

APPLICATION OF ARTIFICIAL INTELLIGENCE TO PREDICT STRENGTH OF CONCRETE

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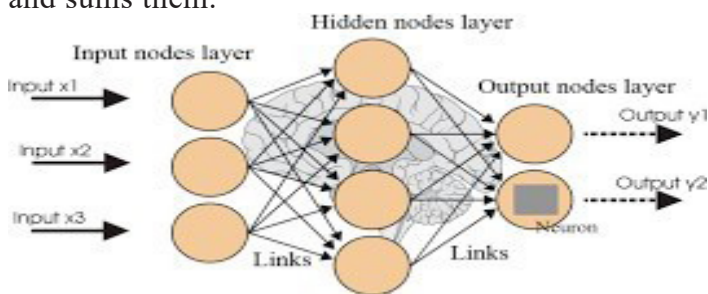
Abstract

Our thirst for progress as humans is reflected by our continuous research activities in different areas leading to many useful emerging applications and technologies. Artificial intelligence and its applications are good examples of such explored fields with varying expectations and realistic results. Generally, artificially intelligent systems have shown their capability in solving real-life problems; particularly in non-linear tasks. Such tasks are often assigned to an artificial neural network (ANN) model to arbitrate as they mimic the structure and function of a biological brain; albeit at a basic level. In this paper, we investigate a newly emerging application area for ANNs; namely structural engineering. We design, implement and test an ANN model to predict the properties of different concrete mixes. Traditionally, the performance of concrete is affected by many non-linear factors and testing its strength comprises a destructive procedure of concrete samples.

Key Words: Artificial Neural Network, Compressive strength, Durability, Ingredients of concrete.

I. INTRODUCTION

Artificial Neural Networks are typical example of modern interdisciplinary subject that helps solving various engineering problem which couldn't solved by traditional method. Neural network capable of collecting, memorizing, analyzing and processing large number of data gained from some experiment. They are an illustration of sophisticated modeling technique that can be used for solving many complex problems. The trained neural network serves as an analytical tool for qualified prognoses of the results, for any input data which were not included in the learning process of the network. Their operation is simple and easy. An artificial neural network is an emulation of biological neural system. It is developed systematically step by step procedure. Input/output training data is fundamental for this network as it conveys information which is necessary to discover the optimal operating point. The weight assigned with each arrow which represent information arrow, to give more or less strength to the signal which they transmit. The input neuron have only one input, their output will input they received multiplied by weight. The neuron on output layer receives output of both input neuron, multiplied by their respective weight and sums them.



REVIEW OF LITERATURE

Yaman et al. 2015 and Taman et al. 2017 represent self compacting concrete is a highly flow able type of concrete that spreads into form without the need of mechanical vibration. It represents a comparative study between two methodologies which have been applied on two different data sets of SCC mixtures, which were gathered from the literature, using artificial neural network (ANN). The two methodologies aim to get the best prediction accuracy for the SCC ingredients using the 28-day compressive strength and slump flow diameters as inputs of the ANN. In the first methodology, the ANN model is constructed as a multi input – multi output neural network with the six ingredients as outputs. In the second methodology, the ANN model is constructed as a multi input – single output neural network where the six ingredient outputs are predicted separately from six different neural networks of multi input – single output type. Also, the influence of the mixes homogeneity on the prediction accuracy is investigated through the second data set. The results demonstrate the superiority of the second methodology in terms of accuracy of the predicted outputs. Hassani et al. 2015 states that pervious concrete is a concrete mixture prepared from cement, aggregates, water, little or no fines, and in some cases admixtures. The hydrological property of pervious concrete is the primary reason for its reappearance in construction. It gives two important aspects of pervious concrete due to permeability and compressive strength are investigated using artificial neural networks (ANN) based on laboratory data. The proposed network is intended to represent a reliable functional relationship between

the input independent variables accounting for the variability of permeability and compressive strength of a porous concrete. Results of the Back Propagation model indicate that the general fit and replication of the data regarding the data points are quite fine. The R-square goodness of fit of predicted versus observed values range between 0.879 and 0.918 for the final model; higher values were observed for the permeability as compared with compressive strength and for the train data set rather than the test data set. The findings can be employed to predict these two important characteristics of pervious concrete when there are no laboratorial data available. Chopra et al. 2015 gives effort has been made to develop concrete compressive strength prediction models with the help of two emerging data mining techniques, namely, Artificial Neural Networks and Genetic Programming. The data for analysis and model development was collected at 28, 56, and 91-day curing periods through experiments conducted in the laboratory under standard controlled conditions. The developed models have also been tested on in situ concrete data taken from literature. A comparison of the prediction results obtained using both the models is presented and it can be inferred that the ANN model with the training function Levenberg-Marquardt (LM) for the prediction of concrete compressive strength is the best prediction tool. Deshpande et al. 2014 gives artificial neural

networks have emerged out as a promising technique for predicting compressive strength of concrete. In the present study back propagation was used to predict the 28 day compressive strength of recycled aggregate concrete (RAC) along with two other data driven techniques namely Model Tree (MT) and Non-linear Regression (NLR). Recycled aggregate is the current need of the hour owing to its environmental friendly aspect of re-use of the construction waste. The study observed that, prediction of 28 day compressive strength of RAC was done better by ANN than NLR and MT. The input parameters were cubic meter proportions of Cement, Natural fine aggregate, Natural coarse Aggregates, recycled aggregates, Admixture and Water (also called as raw data). The study also concluded that ANN performs better when non-dimensional parameters like Sand–Aggregate ratio, Water–total materials ratio, Aggregate–Cement ratio, Water–Cement ratio and Replacement ratio of natural aggregates by recycled aggregates, were used as additional input parameters. Study of

each network developed using raw data and each non dimensional parameter facilitated in studying the impact of each parameter on the performance of the models developed using ANN, MT and NLR as well as performance of the ANN models developed with limited number of inputs. The results indicate that ANN learn from the examples and grasp the fundamental domain rules governing strength of concrete. Gupta et al. 2013 presents application of artificial neural network to develop model for predicting 28 days compressive strength of concrete with partial replacement of cement with nano- silica for which the data has been taken from various literatures. The use of nano-particle materials in concrete can add many benefits that are directly related to the durability of various cementations materials, besides the fact that it is possible to reduce the quantities of cement in the composite. The performance of the model can be judged by the correlation coefficient, mean absolute error and root mean square error have been adopted as the comparative measures against the experimental results obtained from the literature. Muthupriya et al. 2011 represent artificial neural network for predicting compressive strength of cubes and durability of concrete containing metakaolin with fly ash and silica fume with fly ash are developed at the age of 3, 7, 28, 56 and 90 days. For building these models, training and testing using the available experimental results for 140 specimens produced with 7 different mixture proportions are used. The data used in the multi-layer feed forward neural networks models are designed in a format of eight input parameters covering the age of specimen, cement, metakaolin (MK), fly ash (FA), water, sand, aggregate and super plasticizer and in another set of specimen which contain SF instead of MK. According to these input parameters, in the multi-layer feed forward neural networks models are used to predict the compressive strength and durability values of concrete. It shown that neural networks have high potential for predicting the compressive strength and durability values of the concretes containing metakaolin, silica fume and fly ash. Alshihri et al. 2008 this investigation, the neural networks are used to predict the compressive strength of light weight concrete (LWC) mixtures after 3, 7, 14, and 28 days of curing. Two models namely, feed-forward back propagation (BP) and cascade correlation (CC), were used. The compressive strength was modeled as a function of eight variables: sand, water/cement ratio, light weight fine aggregate, light weight

coarse aggregate, silica fume used in solution, silica fume used in addition to cement, super plasticizer, and curing period. It is concluded that neural network model predicated

CONCLUSIONS

Artificial Neural Network (ANN) model is a reliable computational model to solve different complex problems such as prediction problems. The neural network can be used for a particular problem when deviation in the available data is expected and accepted and also when a defined methodology is not available. Therefore, in order to predict the properties of concrete with high reliability, instead of using costly experimental investigation, Artificial Neural Network model can be replaced. The neural network model to predict compressive strength of concrete specimens is utilized in this study. The prediction from values of average percentage error Artificial Neural Network shows a high degree of consistency with experimentally evaluated compressive strength of concrete specimens used. Thus, the present study suggests an alternative approach of compressive strength assessment against destructive testing methods.

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