IJNRD.ORG ISSN : 2456-4184
INTERNATIONAL JOURNAL OF NOVEL RESEARCH AND DEVELOPMENT (IJNRD) | IJNRD.ORG
An International Open Access, Peer-reviewed, Refereed Journal

REAL TIME CONCRETE QUALITY CONTROL ATSITE USING ARTIFICIAL INTELLIGENCE

S.Manikandan[1], P.Jaya karthikreddy[2]

[1](Assistant Professor, Civil Engineering, Panimalar Engineering College, Chennai Email: yuva5555@gmail.com)[1],

[2](UG Scholar, Civil Engineering, Panimalar Engineering College, Chennai) Email: pjayakarthik2001@gmail.com)[2]

Abstract. The application of (AI) is extensively useful in various fields of engineering similarly in this project we have planned to reduce the men power and complexity in traditional concrete quality control, it also reduce the time and laboratory setup at site that will contribute high quality concrete with low cost and less time .in this project we are using the sensors to identify the w/c ratio of concrete, cement, sand, aggregate proportion by inserting the sensor stick in to the fresh concrete ,this parameters are taken into consideration for compressive strength calculation and it will show the compressive strength in digital display attached with sensor stick hence it is very useful in mass industrial and residential concreting this is the innovative method in the this field of civil engineering that will create revolution in industry by quick strength calculation

KEYWORDS –Quality control, Artificial intelligence, Concrete, W/C ratio, Proportion

INTRODUCTION

For many years, deep learning technologies have been successfully applied in many different sectors—civil engineering included. In fact, machine learning technique took the center stage in the industry long ago with the emergence of complex buildings such as skyscrapers. Now more than ever, we see the application and development of AI in the construction industry, which includes the use of intelligent algorithms, big data, and deep learning machines that have transformed productivity performance.

Practicing civil engineers, contractors, and service providers have all been using AI to solve a whole range of problems. For instance, Artificial Intelligence in civil engineering has become more sophisticated, with efficiencies feeding directly into construction processes. AI is also applied in the initial stages of many projects in design optimization, risk control, and improving productivity.

It is imperative to realize construction companies that have already started implementing AI practices are 50% more profitable. More importantly, Artificial Intelligence as a whole has a range of functions in civil engineering. In an age where machines can think rather than just do, engineers can make better judgments while discharging their services more effectively.

2. AIM & OBJECTIVE OF THE STUDY

The main aim of this project is to produce high quality concrete in most economical way using artificial intelligence, the objective of this project is to create an instrument that will detect and analyze the quality of concrete at site quickly

Damage Detection in Concrete Bridge T Girders Using 3-D Finite Element Simulations Trained by Artificial Neural Network

Speaker(s): Hayder Rasheed, Alaaeldin Abouelleil, and Eric Fletcher

The structural deterioration of aging infrastructure systems is becoming an increasingly important issue worldwide. To compound the problem, economic strains limit the resources available for repair or replacement of such systems. Over the past several decades, structural health monitoring (SHM) has proven to be a cost-effective method for the detection and evaluation of damage in structures. Visual inspection and condition rating are one of the most commonly applied SHM techniques, but the effectiveness of SHM varies depending on the availability and experience of qualified personnel and largely qualitative damage evaluations.Simply supported three-dimensional reinforced concrete T-beams with varying geometric, material, and cracking properties were modeled using Abaqus finite element (FE) analysis software.

Up to five cracks were considered in each beam, and the ratios of stiffness between cracked and healthy beams with the same geometric and material parameters were measured at nine equidistant nodes along the beam. A feedforward ANN utilizing backpropagation learning algorithms was then trained on the FE model database with

beam properties and nodal stiffness ratios serving as inputs for the neural network model. The outputs consisted of the predicted parameters of location, depth, and width of up to five cracks.

This inverse problem is very difficult or impossible to solve with the training done by the Artificial Neural Network. One ANN was trained to predict the parameters of the cracks using the full database of FE simulations. The damage prediction ANN achieved fair prediction accuracies, with coefficients of determination (R2) equal to 0.42. This result was the outcome of the no uniqueness in the prediction of this inverse analysis.

Nevertheless, this ANN model provides a rough estimate of the cracking type and damage content in bridge girders once the nodal stiffness ratios are measured or estimated.The Power of Statistical Learning Applied to the Proportioning of Fiber-Reinforced Concrete Mixes Speaker(s): Emilio Taenqua

Fiber-reinforced concrete (FRC) presents flexural load-bearing capacity in the cracked state, and residual flexural strength parameters are the basis of the material's characterization and specification, together with compressive strength. However, the incorporation of fibers also affects the workability of the fresh mix. The correlations between these parameters and the dosage, size, and type of fibers as well as the relative amounts of the other constituents in a FRC mix are usually described separately for different specific mixes, with limited general validity.

Furthermore, residual flexural strength parameters are mutually interdependent, and therefore conventional approaches that regard them as independent variables fail to make the most of the information which extracted from characterization tests results. The project "Optimization of Fiber-Reinforced Concrete using Data Mining" (abbreviated as OptiFRC), funded by the Concrete Research Council / ACI Foundation, has undertaken the first meta-analysis of FRC mixes and their main properties.

An exhaustive database comprising nearly 2,000 cases of FRC mixes and their properties has been compiled from papers published in indexed journals. All this information has been analyzed from a data analytics perspective in order to develop statistical models for the multi-objective optimization of FRC mix designs. Semi-empirical equations have been obtained to relate residual flexural strength, compressive strength, and slump to the FRC mix proportioning, not only in terms of average values but also to account for their variability and sensitivity to changes.

State of the Art on Self-healing Capacity of Cementitious Materials Based on Data Mining Strategies
Speaker(s): Liberato Ferrara, Ali Al-Obaidi, and S. Gupta

Concrete and cement-based materials inherently possess an autogenous self-healing capacity, which is even high in High and Ultra High Performance Concretes (HPC, UHPC) because of the high cement and supplementary cementitious materials (SCM) and low water/binder ratios. Despite the huge amount of literature on the topic self-healing concepts still fail to consistently enter into design strategies able to effectively quantify their benefits of the structural performance.

In this study, quantitative relationships through statistical models have been carried out. The employed approaches aimed at establishing a correlation between the mix proportions, mainly in terms of quantity and type of binders, exposure type, and time and width of the initial crack against suitably defined self-healing indices, quantifying the recovery of material performances which can be of interest for intended applications. Therefore, this study provides, for the first time in the literature to the authors' knowledge, a holistic investigation on the autogenous self-healing capacity of cement-based materials based on extensive literature data mining.

This is also intended to pave the way towards consistence incorporation of self-healing concepts into durability based design approaches for reinforced concrete structures, aimed at quantifying, with reliable confidence, the benefits in terms of slower degradation of the structural performance and extension of the service life-span. The main purpose of the study has been to quantify a "healable crack width" as a function of the structural service scenario as well as of the material composition variables, which could be used in serviceability limit state design calculations as well as quantify its influence on material

durability parameters with the purpose of evaluating the kinetics of degradation mechanisms. The final aim of the study is to propose, also through suitably built design charts, a straightforward input-output model to quickly predict.

Autonomous Evaluation of Fire-damaged Concrete Structures
Speaker(s): M. Z. Naser

We, as civil engineers, and practitioners, continue to favor traditional methods to assess the state of damaged

structures in the aftermath of an extreme event (fire, earthquake etc.). Not only that these methods provide us with bare qualitative/opinion-based assessment, but also require the allocation of tremendous resources as well as physical presence of on-site experts – a condition that may not be possible in many scenarios (i.e. remote areas, toxicity/temperature, fear of imminent collapse etc.). The majority of these limitations can be overcome by leveraging recent technological advancements in parallel fields (i.e. computer science, robotics, sensing etc.).

This article showcases how such technologies can be adopted to realize a modern, safe, instant, and realistic (quantitative) evaluation of damaged concrete structures. More specifically, this article explores concepts for autonomous assessment (AA) via computer vision (CV) and machine learning (ML) techniques and how AA can be used to; (1) identify failure mechanisms, and (2) propose suitable repair strategies.

In the proposed model, βi is a regression coefficient (i= 1,2,3,…,n), X's values represent Artificial Intelligence Methods

Artificial Neural Network (ANN)
ANN is a computational model that tries to simulate the structure and functional aspects of biological neural networks. Various ANN applications can be categorized as classification models or regression models. The use of ANN specifically to predict the compressive strength of concrete has been intensively studied [1, 6]. The researchers also explored the use of ANN to build concrete compressive strength models that were more accurate than the regression model. The most used ANN model is the multilayer perception (MLP) model. In the MLP model, the input layer contains a set of sensory input nodes, one or more hidden layers that function ate to compute, and the output layer contains one computational node that represents the concrete compressive strength. The most commonly used and effective learning algorithm for training the MLP model is a back-propagation (BP) algorithm. The activation process of each neuron can be seen in Equations (1) and (2).

$$netk = \sum wkjoj \quad (1)$$

$$yk = f\,(netk) \quad (2)$$

Where $netk$ is the activation of neurons to k, j is the set of neurons in the previous layer. wkj is the weight of the connection between neurons k and neurons j, oj is the output of neurons j, and yk represents the output that is usually calculated in sigmoid and logistical transfer functions. Illustration of ANN structure can be seen through Figure 1.

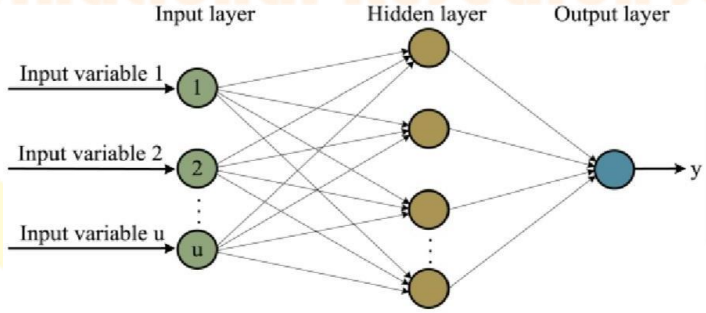
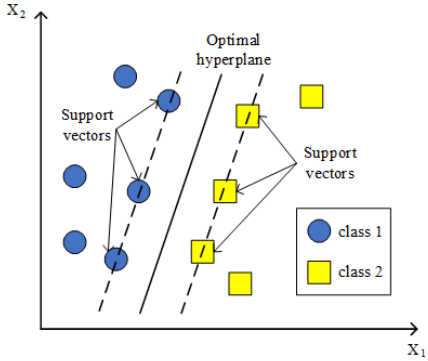


Figure 1. Illustration of ANN structure.

Support Vector Machine (SVM)
SVM was first introduced by Vapnik (1995) [13]. SVM has been used in many civil engineering applications, and in recent years, it has often been used to predict concrete compressive strength [14- 16]. In this study, support vector regression (ε-SVR), which is a variation of SVM, is used to build an input-output model from concrete. SVM uses an objective function that allows the function estimation process to occur, as illustrated in Figure 2. When nonlinear space occurs, the kernel radial-based function (RBF) i SVM because it can provide better results than the other kernels.

1. Data input: This step is the first step where data collection will be taken.
2. Training and testing: Input data will be divided into 2 data groups, namely, training and testing. Training is used to



create prediction models that fit the data while testing is used to test prediction models that are built. In this study, 70% of the data will be used for training, and 30% of the data will be used for testing.
3. The learning process of AI prediction models with training data.
4. The process of testing AI prediction models with data testing.
5. Prediction results: The four accuracy indicators will be used to measure the performance of the predicted results obtained for each model.

Figure 4 explains the flow diagram to building the AI prediction using a single model.

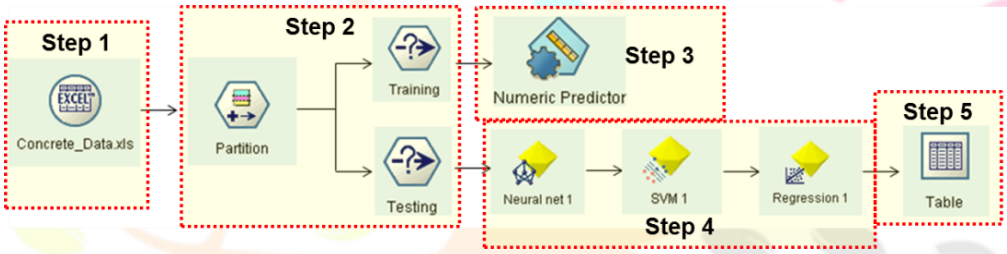


Figure 4. Flow diagram of the formation of AI prediction using a single model.

The simplest method of combining multiple classifiers is voting. In the cases of prediction, the outputs of the individual classifiers are pooled. Then, the class which receives the largest number of votes is selected as the final classification decision. In general, the numerical output can be determinedby different combinations of probability estimates [17]. By combining two or three different individualclassifiers, this study obtained four different ensemble classifiers. Ensemble of two different classifiers selected as a kernel function in

Conclusion

This study presents a comparative study between two construction models, namely the single model and ensemble models, in predicting the concrete compressive strength based on 1030 concrete samples. These samples were used to form a database that was used to create a prediction model as well as to test the accuracy of the prediction model formed. Four accuracy indicators are used in evaluating the performance of each method, including R, RMSE, MAPE, and MAE. Experiments werecarried out using Clementine 12.0 software. The finding showed that ANN achieved the best accuracy for all performance measures because it can provide the most optimal performance when viewed from the four indicators. This research succeeded in proving that AI methods are able to predict concrete compressive strength without conducting experiments in the laboratory with good accuracy.

References

[1] Porter ML, Ekberg CE. ―Design recommendations for steel deck floor slabs‖. Journal of the Structural Division 1976; vol 102(11):pp21–36.
[2] Wright HD, Evans HR, Harding PW. The use of profiled steel sheeting in floor construction‖. Journal of Constructional Steel Research 1987;7(4):279–95.
[3] Jolly CK, Zubair AKM. ―The efficiency of shear–bond interlock between profiledsteel sheeting and concrete‖. International conference on steel and aluminium structures, Cardiff. London: Elsevier; 1987. pp. 27–36.
[4] Wright HD. ―Composite slabs. Progress in Structural Engineering and Materials‖1998;1(2):178–84.
[5] Eurocode 4: ―design of composite steel and concrete structures, part 1.1: generalrules and rules for buildings‖. EN1994-1-1:2004. Brussels: European Committee forStandardization; 2004.
[6] ASCE. Standard for the structural design of composite slabs. ANSI/AASCE3-91. New York: American Society of Civil Engineers; 1992.

[7] Abdullah R, Easterling WS. Determination of composite slab strength using a new elemental testmethod. Journal of Structural Engineering, ASCE 2007 vol;133(9):pp 68–77.

[8] AbdullahR,Easterling WS.Newevaluationandmodeling procedure for horizontal shear bond in composite slabs. Journal of Constructional Steel Research 2009; vol 65(4):pp 891– 902.

[9] Chen S. Load carrying capacity of composite slabs with various end constraints.Journal of Constructional Steel Research 2003 vol-59(3):pp 385–403.

[10] Daniels BJ, Crisinel M. Composite slab behavior and strength analysis. Part I:calculation procedure. Journal of Structural Engineering, ASCE 1993; vol 119(1) pp16–35.