# An Elaborated Study of High Performance Concrete Structures Built

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**Abstract – In the search for durability, researchers and in other countries sought for higher performance materials. Technology from other countries, notably France, Norway, Japan and Germany, was incorporated into developments. High Performance Concrete (HPC) was included in this research. With the establishment in 1990, a co-ordinated and concentrated programme of research commenced. In 1994, this programme expanded to include demonstration projects to implement HPC technology on construction sites. Technology Transfer was a primary goal of CC. Many seminars, workshops and technology transfer days were held across Canada, by CC alone, in co-operation with American Concrete Institute (ACI) Chapters, the Cement Association of Canada (CAC) and its member companies, and for specific entities such as Provincial Highway Departments and Cities. Between 1990 and 2000, CC researchers published over 400 Papers in scientific journals. It seemed appropriate, as the old millennium ended, to assess the practice in the use of HPC over the past 10 years. The extent of its use, the varying specifications, results, economics and problems encountered have been reviewed. Looking ahead, areas for ongoing research and development have been identified. The study demonstrates that, for those who have correctly implemented this technology, HPC is the high quality concrete of choice for high strength, durability and optimum lifecycle costs.**

**Index Terms – HPC, CC, ACI, CAC, Durability.**

## 1. INTRODUCTION

High Performance Concrete is a term used to describe concrete with special properties. HPC was first known to be concrete with high strength for structural purpose. However, advances in concrete technology have generated a new (Super plasticizer, retarders, flyash, blast furnace slag, silica fume, fumed silica and metakaolin) combined according to a selected mix design, properly mixed, transported, placed, consolidated and cured to give excellent performance, such as high compressive strength, high density, low shrinkage, high modulus of elasticity, low permeability, and good resistance to certain forms of attack. Most ready-mixed concrete producers are familiar with the concept of "performance concrete." performance concrete implies that specifications will stipulate minimum concrete strengths and leave the proportioning of the concrete mixture to the concrete producer .However, lately, another similar term, "high-performance concrete," is being heard in the industry.

### 1.1. High-Performance Concrete

In 1990, researchers at the Strategic Highway Research Program (SHRP) defined a HPC as concrete meeting one of the following requirements:

- ✓ 4-hour compressive strength > 3,000 psi
- ✓ 24-hour compressive strength > 5,000 psi
- ✓ 28-day compressive strength > 10,000 psi
- ✓ Water-cementitious materials ratio < 0.35

Also, the concrete must have a durability factor greater than 80 after 300 cycles of freezing and thawing to meet their definition, The American Concrete Institute (ACI) formed a special committee on HPC in 1992. This committee has taken a broader view of HPC to include performance aspects other than compressive strength in its definition (this definition is similar to an earlier definition proposed by the National Institute of Standards and Technology): Concrete meeting special performance and uniformity requirements which cannot always be achieved routinely using only conventional constituents and normal mixing, placing and curing practices

Developments in mineral and chemical admixtures have made it possible to produce concretes with relatively much higher strengths than was thought possible. Presently concrete with strengths of 90 to 112 MPa are being commercially produced and used in the construction industry in many countries. Several researchers have tried different mineral admixtures like flyash FA), pulverized fuel ash (PFA), silica fume (SF), Metakaolin (MK), and ground granulated blast furnace slag (GGBS) in producing HPC. The search is still going on for identifying different mineral admixtures for improving the cementitious properties so that high compressive and flexural strengths can be achieved.

### 1.2. Neural network

The first journal article on neural network application in civil/structural engineering was published in this journal in 1989. This article reviews neural network articles published in archival research journals since then. The emphasis of the

review is on the two fields of structural engineering and construction engineering and management. Neural networks articles published in other civil engineering areas are also reviewed, including environmental and water resources engineering, traffic engineering, highway engineering, and geotechnical engineering. The great majority of civil engineering applications of neural networks.

Applications of other recent, more powerful and efficient neural-networks models are also reviewed. Recent works on integration of neural networks with other computing paradigms such as genetic algorithm, fuzzy logic, and wavelet to enhance the performance of neural network models are presented. Artificial neural networks (ANNs) are a family of massively parallel architectures that are capable of learning and generalizing from examples and experience to produce meaningful solutions to problems even when input data contain errors and are incomplete. This makes ANNs a powerful tool for solving some of the complicated engineering problems. Basically, the processing elements of a neural network are similar to the neuron in the brain, which consists of many simple computational elements arranged in layers.

### 1.2.1. Back propagation

Back propagation was created by generalizing the Widrow-Hoff learning rule to multiple-layer networks and nonlinear differentiable transfer functions. Input vectors and the corresponding target vectors are used to train a network until it can approximate a function, associate input vectors with specific output vectors, or classify input vectors in an appropriate way as defined by you. Networks with biases, a sigmoid layer, and a linear output layer are capable of approximating any function with a finite number of discontinuities.

Properly trained back propagation networks tend to give reasonable answers when presented with inputs that they have never seen. Typically, a new input leads to an output similar to the correct output for input vectors used in training that are similar to the new input being presented. This generalization property makes it possible to train a network on a representative set of input/target pairs and get good results without training the network on all possible input/output pairs. There are two features of the Neural Network Toolbox that are designed to improve network generalization: regularization and early stopping. These features and their use are discussed in “Improving Generalization”.

### 1.2.2. Feed Forward Networks

In a feed forward neural network, the artificial neurons are arranged in layers, and all the neurons in each layer have connections to all the neurons in the next layer. However, there is no connection between neurons of the same layer or the neurons which are not in successive layers. The feed forward network consists of one input layer, one or two hidden layers and one output layer of neurons. Associated with each connection between these artificial neurons, a weight value is defined to represent the connection weight. Shows a typical architecture of a multilayer feed forward neural network with an input layer, two hidden layer, and an output layer. The input layer receives input information and passes it onto the neurons of the hidden layer(s), which in turn pass the information to the output layer. The output from the output layer is the prediction of the net for the corresponding input supplied at the input nodes. Each neuron in the network behaves in the same way as discussed.

## 2. RELATED WORK

The most important step in designing neural network model is identification the nature of problem that we are going to solve. This will determine the selection of suitable network topology. Neural network model is defined by its topology, learning paradigm and learning topology [8]. For this study, only certain network topologies were suitable to perform the required function in solving the domain problem. The next step is to identify the types of input data whether it is all binary (0/1), bipolar (- 1/+1) or the data contains real-value inputs. These types of data might disqualify some of the network architecture which used certain activation functions in their learning algorithm. The last step is to determine the number of nput and output units and the hidden nodes that gives the best performance. The problem of this study is to classify the mixture proportioning of high performance concrete that can give a required strength based on various factors. Therefore the designed network must be able to solve the classification problem. The network has to map the features of the inputs and produce the desired output. Therefore the network has to use supervised training approach. Since the prepared data contains real-values between 0 and 1, the most suitable activation function is binary sigmoid function. This selected function is suitable to use in back propagation learning algorithm.

The basic strategy for developing a neural network-based model for material behavior is to train a neural network on the results of a series of experiments using that material. If the experimental results contain the relevant information about the material behavior, then the trained neural network will contain sufficient information about material’s behavior to qualify as a material model (Hakim, Mesri and Selaru). Such a trained neural network not only would be able to reproduce the experimental results, but also it would be able to approximate the results in other experiments through its generalization capability.

Application of the water absorption as a criterion for the Durability of Concrete structures in marine environments this paper presents laboratory obtained data of the water absorption and electrical resistivity of Concrete specimens with twenty mixture proportions containing Silica Fume subjected to different curing methods. According to the results, there is a

good correlation between water absorption and electrical resistivity of Concrete. This study was conducted to investigate the relation between water absorption and electrical resistivity of concrete with different w/c ratios containing Silica Fume, which were cured at different regimes. According to the results the following conclusions can be drawn: Increasing in w/c ratio not only reduces the compressive strength, but also increases the water absorption of concrete. The electrical resistivity of concrete increases with reducing the w/c ratio. There is a good correlation between water absorption and electrical resistivity of concrete. This can be due to this fact that both characteristics are related to microstructure of concrete. However the water absorption method is a test for the assessment of the durability of concrete. The data presented in this paper, are primary results of laboratory experiments of a long-term project in Persian Gulf. Supplementary experiments are conducting to investigate other aspects of this matter. The results will be published in future.

Present improved perceptron learning algorithm by introducing an adjustment factor in each self-modification iteration of the original perceptron learning model. The adjustment factor in each iteration is determined such that the domain error is reduced in the subsequent iterations. This leads to global improvement in the iterative process toward ending the weight vector. The application of the new algorithm to the steel beam design problem demonstrates that the number of iterations needed for convergence of the vector is substantially fewer than that using the original perceptron algorithm.

The behaviour of a beam-column joint was investigated experimentally and analytically where empirical relationships established by Nijar for the structural behaviour of cast – in – situ beam column joints under static loading conditions. The study investigates the relationship between the behaviour of beam – column joints and geometrical shape, amount and size of steel reinforcement, fixed beam and column cross – sectional dimensions and concrete building frames, provided guidance in the selection of the test specimen dimensions. The corner beam – column joint was subjected to a complex stress distribution due to the effect of biaxial forces. The members were designed according to the British code of practice of the 1972 and checked by the American Concrete Institute, ACI code and the first recommendation of the ACI-ASCE Committee Report.

## 3. SYSTEM DESIGN

The implementation of a neural network tool requires the setting up of training and test data for each individual task and the selection of correct parameters that the network requires to provide a reasonable and acceptable trained network. The methodology process of implementing a neural network, involving two main stages; preprocessing and post-processing. The methodology process of implementing neural network in prediciting parameters involves:

### 3.1. Gathering of Necessary Data

The process involves collecting the required data in one place by generating a FORTRAN program or using a mathematical package such as MATLAB for each specific task. Then separate the data into two sets, one for training and the other for testing. The testing data is normally taken between 9% or 10% of the whole data such that the $9^{th}$ or $10^{th}$ element of training set is reserved for the testing data which will provide the best picture representations that increase confidence in the performance of the trained network.

### 3.2. Approach For Data Selling

Transform the input data to acceptable values to the network; the neural network accepts only values from 0 to 1 for the sigmoid function and -1 to 1 for the hyperbolic tangent function. The input and test sets are normalized by a specific tool within the neural networks under the Minmax table. The calculation involves the computation of low and high values of each training and test example data field in the selected data files and stores them in the Minmax table.

### 3.3. SELECTION OF NETWORK REQUIREMENTS

A back propagation network is a general purpose network that can be implemented for prediction, classification, and system monitoring, filtering and solving other problems. The advantages of the back propagation network are the use of non-linear regression techniques that attempt to minimize global error, its ability to provide compact distribution representations of complex data and its potential to manipulate multiple – dimensional functions.

### 3.4. NEURODYNAMICS RULES

Neurodynamics represents the learning rules and transfer activation functions that represent a specific network. One of the most popular learning rules used by back propagation network is the Generalized-Delta-Rule developed by Rumelhart, Hinton and Williams. Extensions of the generalized delta rule implemented in the Neural works tool are the cumulative –Delta – Rule which accumulates weights changes over several examples and the Normalized Cumulative Delta rules.

The Neural Works tool incorporates five types of activation functions; sigmoid, hyperbolic tangent, sine, linear, and Digital Neural Network Architecture (DNNA) functions. The selection of a transfer function is entirely determined by the type of data and the requirements of the network. The recommended activation functions are the sigmoid activation function which is best for learning about an “average” behaviour while the hyperbolic tangent activation function is suited for learning about “deviation” from the average.

## 4. IMPLEMENTATION METHODOLOGY

**4. 1. Process of Training and Testing the Network**

Selecting the correct network configuration has a substantial impact on the network results. The basic training processing involves the presentation of the input data with the desired output. The network then adjusts its internal by carrying out an iteration procedure to correct the error to produce acceptable results. This iteration process continues until it runs for a specific time or the network converges to acceptable levels. Usually, the number of iterations is specified as the number of learning's in the run menu, or as an acceptable error in RMS diagnosis tool. Once the network is trained and coverage's, the test set is presented to the network sequentially only once to increase the confidence of the network performance and accounts for accuracy. During the process of learning the network is monitored visually by graphical instruments provided by the software to observe the learning process and to adjust any configurations that might arise.

**4 .2. Network Monitoring**

The network performance is monitored during training by confusion matrix, weight histogram, Root – Menu-Square (RMS) and classification rate diagnostic instruments provided by the tool to achieve a better understanding of the network performance. The confusion matrix is a visual display diagnostic instrument used to monitor the performance of each network output processing element and compares it to the desired output. The x-axis along the confusion matrix provides the network output while the y-axis provides the desired output. The interior Quadrants are discredited into bins to show the network outputs. A value of one means an excellent correlation between the desired and network output.

**4. 3. Network Optimization Requirements**

Network performance is crucial which a part of optimization process is after the network is set and trained. This can be done by tuning the internal layer size, epoch size and learning rates to obtain reliable network.

**4. 4. Deployment of workable Network**

The final network can be deployed as part of the system application after it is completely trained and tested. This can be accomplished by either converting the trained network into a 'C' subroutine provide by the Flash Code and linking it with a main 'C' source code or by entering data interactively through the keyboard and getting results instantaneously, However, for a large number of input and test sets, an input ASCII file can be called within the Neural works since the interactive is not recommended due to its prolonging of entering data and the possibility of entering the wrong data.

**4. 5. Development of Trained Networks**

The trained deployed networks require continuous monitoring and maintenance during implementation to check reliability. Developing and debugging the trained, testing and creating maintenance are part of the network development which allows computers to perform tasks that would otherwise require human input and attention.

**4. 6. Numerical methods in engineering with Matlab**

Numerical Methods in Engineering with MATLAB is a text for engineering students and a reference for practicing engineers, especially those who wish to explore the power and efficiency of MATLAB. The choice of numerical methods was based on their relevance to engineering problems. Every method is discussed thoroughly and illustrated with problems involving both hand computation and programming. MATLAB M-files accompany each method and are available on the book web site. This code is made simple and easy to understand by avoiding complex book-keeping schemes, while maintaining the essential features of the method. MATLAB was chosen as the example language because of its ubiquitous use in engineering studies and practice. Moreover, it is widely available to students on school networks and through inexpensive educational versions. MATLAB a popular tool for teaching scientific computation.

MATLAB is a high-level computer language for scientific computing and data visualization built around an interactive programming environment. It is becoming the premiere platform for scientific computing at educational institutions and research establishments. The great advantage of an interactive system is that programs can be tested and debugged quickly, allowing the user to concentrate more on the principles behind the program and less on programming itself. Since there is no need to compile, link and execute after each correction, MATLAB programs can be developed in much shorter time than equivalent FORTRAN or C programs. On the negative side, MATLAB does not produce stand-alone applications—the programs can be run only on computers that have MATLAB installed.

## 5. RESULTS AND DISCUSSION

**5.1. Formulation**

In this study, the error arose during the training and testing in ANN-I and ANN-II models can be expressed as a root-mean squared (RMS) error and is calculated by Equation

$$\text{RMS}=\sqrt{\frac{1}{p}\sum_i [t_i - o_i]^2} \qquad (5.1)$$

In addition, the absolute fraction of variance (R2) and mean absolute percentage error (MAPE) are calculated by below Equation

$$R^2 = 1 - \left( \frac{\sum_i (t_i - o_i)^2}{\sum_i (o_i)^2} \right) \qquad (5.2)$$

$$\text{MAPE}=\left|\left(\frac{t_i - o_i}{o_i}\right)\right| * 100 \qquad (5.3)$$

Here t is the target value, o is the output value, p is the pattern. In the training and testing of ANN-I and ANN-II models, various experimental data from two different sources are used. In the ANN-I and ANN-II models, 130 data of experiment results were used for training whereas 65 ones were employed for testing. All results, obtained from experimental studies and predicted by using the training and testing results of ANN I and ANN II models, for 3, 7, 28, 56 and 90 days fc were given respectively. The linear least square fit line, its equation and the R2 values were shown in these figures for the training and testing data. Also, inputs values and experimental results with testing results obtained from ANN-I and ANN-II models were given in Table 3.1 values obtained from the training and testing in ANN-I and ANN-II models are very closer to the experimental results. The result of testing phase ANN-I and ANN-II models are capable of generalizing between input and output variables with reasonably good predictions.

Table.1 testing data sets for comparison of excremental results with ANN testing predicted models

| AS (day) | C (kg/m$^3$) | MK (kg/m$^3$) | SF (kg/m$^3$) | W (kg/m$^3$) | A (kg/m$^3$) | S (kg/m$^3$) | SP (l/m$^3$) | Experimental results | ANN-I | ANN-II |
|---|---|---|---|---|---|---|---|---|---|---|
| 3 | 571.91 | 0 | 0 | 0.3 | 1171.8 | 609.72 | 6.97 | 35.67 | 37.45 | 35.67 |
| 3 | 529.01 | 7.5 | 42.87 | 0.3 | 1171.8 | 600.27 | 9.30 | 41.00 | 43.2 | 41.12 |
| 3 | 514.72 | 10 | 57.16 | 0.3 | 1171.8 | 597.12 | 9.76 | 39.67 | 38.16 | 39.31 |
| 7 | 571.91 | 0 | 0 | 0.3 | 1171.8 | 609.72 | 6.97 | 41.67 | 43.26 | 41.23 |
| 7 | 529.01 | 7.5 | 42.87 | 0.3 | 1171.8 | 600.27 | 9.30 | 49.33 | 52.4 | 49.15 |
| 7 | 514.72 | 10 | 57.16 | 0.3 | 1171.8 | 597.12 | 9.76 | 43.33 | 46.21 | 43.24 |
| 28 | 571.91 | 0 | 0 | 0.3 | 1171.8 | 609.72 | 6.97 | 54.67 | 54.15 | 54.67 |
| 28 | 529.01 | 7.5 | 42.87 | 0.3 | 1171.8 | 600.27 | 9.30 | 59.00 | 59.54 | 59.00 |
| 28 | 514.72 | 10 | 57.16 | 0.3 | 1171.8 | 597.12 | 9.76 | 55.67 | 55.21 | 55.61 |
| 56 | 571.91 | 0 | 0 | 0.3 | 1171.8 | 609.72 | 6.97 | 61.33 | 61.35 | 61.33 |
| 56 | 529.01 | 7.5 | 42.87 | 0.3 | 1171.8 | 600.27 | 9.30 | 66.36 | 62.45 | 66.35 |
| 56 | 514.72 | 10 | 57.16 | 0.3 | 1171.8 | 597.12 | 9.76 | 62.67 | 63.22 | 62.64 |
| 90 | 571.91 | 0 | 0 | 0.3 | 1171.8 | 609.72 | 6.97 | 70.00 | 71.35 | 70.00 |
| 90 | 529.01 | 7.5 | 42.87 | 0.3 | 1171.8 | 600.27 | 9.30 | 77.33 | 75.61 | 77.32 |
| 90 | 514.72 | 10 | 57.16 | 0.3 | 1171.8 | 597.12 | 9.76 | 71.00 | 72.03 | 71.15 |

Table. 2. Testing data sets for water absorption of excremental results with ANN testing predicted model

| Mix | % of SF | % of Flyash | Water Absorption (%) In 24 Hrs | Water Absorption In ANN-I | Water Absorption In ANN-II | % of error difference |
|---|---|---|---|---|---|---|
| M1 | 0 | 0 | 2.00 | 1.92 | 2.01 | 0.49 |
| M2 | 5 | 0 | 1.96 | 1.86 | 1.96 | 0 |
| M3 | 7.5 | 0 | 1.94 | 1.87 | 1.94 | 0 |
| M4 | 10 | 0 | 1.85 | 1.82 | 1.82 | 1.6 |
| M5 | 5 | 10 | 1.20 | 1.01 | 1.20 | 0 |
| M6 | 7.5 | 10 | 1.10 | 0.98 | 1.10 | 0 |
| M7 | 10 | 10 | 1.05 | 0.93 | 1.04 | 0.96 |

Table.3. Testing data sets for acid resistance of excremental results with ANN testing predicted models

| Mix | Dry Weight | Weight After Immersing in Acid (HCl) | Weight Loss (%) | Weight Loss In ANN-I | Weight Loss In ANN-II | % of error difference between experimental and ANN values |
|---|---|---|---|---|---|---|
| M1 | 2.45 | 2.4 | 2.08 | 1.98 | 2.07 | 0.48 |
| M2 | 2.425 | 2.4 | 1.03 | 1.21 | 1.03 | 0 |
| M3 | 2.45 | 2.425 | 1.03 | 1.25 | 1.04 | 0.96 |
| M4 | 2.45 | 2.4 | 1.96 | 1.83 | 1.97 | 0.48 |
| M5 | 2.425 | 2.4 | 1.03 | 0.98 | 1.03 | 0 |
| M6 | 2.55 | 2.5 | 1.96 | 1.87 | 1.96 | 0 |
| M7 | 2.625 | 2.6 | 0.952 | 0.957 | 0.956 | 1.04 |

Table.4. Testing data sets for Permeability of excremental results with ANN testing predicted models

| Replacement percentage | Permeability coefficient x $10^{-7}$ cm/sec | | Permeability coefficient x $10^{-7}$ cm/sec ANN-I | Permeability coefficient x $10^{-7}$ cm/sec ANN-II |
|---|---|---|---|---|
| | Silica Fume | Silica Fume & 10%Fly ash | | |
| 0% | 7.90 | 7.90 | 7.59 | 7.91 |
| 5% | 7.30 | 7.50 | 7.45 | 7.5 |
| 7.5% | 6.90 | 7.10 | 7.2 | 7.1 |
| 10% | 6.50 | 6.60 | 6.55 | 6.60 |

The performance of the ANN-I and ANN II models for fc are finding with the help of MATLAB .MATLAB is a powerful language for technical computing. MATLAB is widely used in universities and colleges in introductory and advanced courses in mathematics, science and especially in engineering. In industry the software is used in research, development and design. The standard MATLAB program has tools (functions) that can be used to solve common problems. In addition, MATLAB has optional toolboxes that are a collection of specialized programs designed to solve specific types of problems. The statistical values for all the station such as RMS, R2 and MAPE, both training and testing, While the statistical values of RMS, R2 and MAPE from training in the ANN-I model were found as 2.5423, 99.53% and 3.524%, respectively, these values were found in testing as 3.1735, 99.15% and 4.435%, respectively. Similarly, while the statistical values of RMS, R2 and MAPE from training in the ANN-II model were found as 1.8452, 99.95% and 2.4762%, respectively, these values were found in testing as 2.9618, 99.86% and 3.5979%, respectively. The best value of R2 is 99.96% for training set in the ANN-II model. The minimum value of R2 is 99.87% for testing set in the ANN-I model. All of the statistical values of the proposed ANN-I and ANN-II models are suitable and predict the 3, 7, 28, 56 and 90 days fc values very close to the experimental values.

## 6. CONCLUSION

Development of neural network simulator model for workability (measured by slump) and compressive strength (measured by compressive test) for HPC incorporating silica fume, fly ash and metakolin is described. The suggested ANN simulator models provide an efficient and rapid means of obtaining optimal solutions to predict the optimum mix proportions for specified strength and workability for sustainable HPC. It is possible to produce HPC mix design with various compositions for a given range of targeted slumps and compressive strength. The developed neural network simulator model by using the back propagation architecture has demonstrated its ability in training the given input/output patterns. The application of artificial intelligence in the field of HPC mix design is very appropriate in order to preserve and disseminate valuable experience and innovation efficiently at reasonable cost.

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