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Predicting concrete properties using neural networks (NN) with principal component analysis (PCA) technique

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Abstract. This paper discusses the combined application of two different techniques, Neural Networks (NN) and Principal Component Analysis (PCA), for improved prediction of concrete properties. The combination of these approaches allowed the development of six neural networks models for predicting slump and compressive strength of concrete with mineral additives such as blast furnace slag, fly ash and silica fume. The Back-Propagation Multi-Layer Perceptron (BPMLP) with Bayesian regularization was used in all these models. They are produced to implement the complex nonlinear relationship between the inputs and the output of the network. They are also established through the incorporation of a huge experimental database on concrete organized in the form Mix-Property. Thus, the data comprising the concrete mixtures are much correlated to each others. The PCA is proposed for the compression and the elimination of the correlation between these data. After applying the PCA, the uncorrelated data were used to train the six models. The predictive results of these models were compared with the actual experimental trials. The results showed that the elimination of the correlation between the input parameters using PCA improved the predictive generalisation performance models with smaller architectures and dimensionality reduction. This study showed also that using the developed models for numerical investigations on the parameters affecting the properties of concrete is promising.

Keywords: neural networks; principal component analysis; correlation; prediction; concrete; additives.

1. Introduction

There are four basic components of concrete: cement, water, coarse aggregates and fine aggregates. Therefore, modeling such a concrete is a four-parameter modeling problem. Adding other mineral additives such as blast furnace slag, fly ash and silica fume and other chemical admixtures such as superplasticizer and air entraining makes this a nine-parameter modeling problem and much more difficult for concrete mix proportioning and predicting its properties. Therefore, concrete mix design involves the choice of components proportions that will result in some desired properties. Most methods of formulating concrete identify slump at the fresh state and compressive strength at the hardened state as the main properties of concrete.

Conventional methods to predict the compressive strength of concrete are based on statistical analysis by which many linear and nonlinear regressions equations were constructed to model a

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predictive problem (Snell and Wallace 1989). For early ages concrete, the literature highlights two methods for the development of the maturity function, which later led to the establishment of a strength-maturity relation first introduced by Saul and Nurse in 1949. Later D'Aloia and Chanvillard (1994) describe a model for predicting early age concrete compressive strength by applying the time equivalent method. Usually, the compressive strength at early age is incorporated into 28 days compressive strength equation (BRE 1988). For predicting the 28 days compressive strength of concrete, many contributions, models and methods were developed from the Ferret or Bolomey formulas (Bolomey 1995, De Lerrard *et al.* 1997, Lawrence and Ringo 2000). Other models were developed based on other approaches (Joe and Eng 1995, Lecomte and De Larrard 2001). However, modelling and predicting rheological properties of concrete is scarce because of its complex behaviour. Recently, the early-age properties of cement based materials have been reviewed by Bentz (2008).

In recent years, Artificial Intelligence (AI) which differs fundamentally from the traditional methods has been widely used to solve complex nonlinear problems in civil engineering and has proven to be remarkably successful particularly in concrete technology by applying different approaches: Expert Systems (ES), Neural Networks (NN), Fuzzy Logic (FL) and Genetic Algorithms (GA) (Zain *et al.* 2005, Yeh 2006, Bilim *et al.* 2009, Uygunoglu and Unal 2006, Jayaram 2009). The application of these approaches contributes to the improvement of existing models and conventional methods for the formulation of concrete and the prediction of its performance. There has been an increasing interest for the use of NN approach. More recently, several researchers moved towards the adoption of this approach for the development of more sophisticated systems in combination with ES, FL and GA (Gupta 2006, Topc and Sardemir 2008, Xiaodong *et al.* 2007) on one hand, and probabilistic, and Bayesian techniques (Lee 2009, Slonski 2007) on the other hand. These techniques have effectively improved NN performance by the derivation of more efficient learning algorithms. However, only few investigations were carried out on the application of a practical technique and intelligent manipulation for the analysis of all the data before learning a NN model which may contain redundancies and correlations between them (Bellamine and Elkamel 2008, Junita and Brian 2008). This represents a very important step before designing a model.

The main objective of this paper is to explore the feasibility of combining both approaches of Neural Networks (NN) and Principal Component Analysis (PCA) to predict slump and compressive strength of concrete. The type of concrete considered here is a concrete containing mineral additives such as slag, fly ash and silica fume. Data were obtained from laboratory tests and literature. The PCA is used as a statistical tool for the elimination of correlations between the data as well as reducing the representation size of these data or data compression. For this reason, six neural networks models were developed and expanded with their input parameters which are the data compressed by the PCA. These models are further improved to create the best network model for each problem. This is done by studying the effect of the parameters used in the construction of networks. Such a program can be used to study effectively the effects of different constituents of the mixture on concrete properties.

2. Neural networks

A neural network is a system composed of a set of neurons interconnected with each other. A certain disposition of the connection of these neurons produced a neural network model suitable for

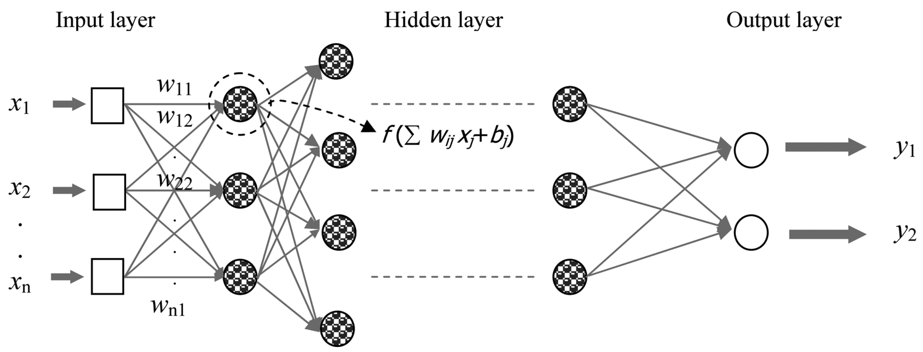


Fig. 1 Multi layer neural network

certain tasks. The Back Propagation Multilayer Perceptron (BPMLP) is the most popular neural network model often used, consisting of three adjacent layers, input, hidden and output (Dreyfus 2002). Each layer contains several neurons (Fig. 1). The NN is trained by presenting a set of input-output associated data based on learning or training process. The training process uses an algorithm, in which the NN develops a function between the inputs and outputs. Generally, in a training process, neurons receive input from the external environment (x_1, x_2, ... x_n) and transmit them to the neurons in the hidden layer, which are responsible for simple and useful mathematical calculations involving the connections weight (w_{11}, w_{12} ..., w_{1n}), bias (b_1, b_1, …, b_n) and input values. The result of these hidden neurons is passed through a threshold or activation function (f) in each neuron (processing element) which limits the output of the neuron with a minimum and maximum allowed bounds. The choice of this function appears to be a very important element in NN, and often nonlinear functions will be required. Once, this function is applied, the final results are produced. Thereafter these results become the input to all neurons in the adjacent layer (the second hidden layer or output layer), and the calculation process is repeated through the layers until the output layer. The output values are produced with output neurons (y_1, y_2 in Fig. 1). At this stage, a value of output error is calculated between the outputs produced and the desired outputs in a supervised learning. Generally, the training process is iterative and stops when a designed error is reached. Upon completion of a training process, the network should be able to give out the solution (s) for any set of data based on the general architecture that has been developed.

The performance of a BPMLP relies heavily on its ability of generalization, which, in turn, depends on the data representation. An important feature of data representation is the de-correlation of these data. In other words, a set of data presented at a BPMLP should not consist of correlations between them because the correlated data reduce the distinctiveness of the representation of data, and therefore, introduce confusion to the model during the learning process and, thus, produces a BPMLP with a low ability to generalization for new data (Bishop 1994). This suggests the need to eliminate the correlation of data before they are presented at a BPMLP. This can be achieved by applying the PCA technique on all input data before the training process of the BPMLP (Jolliffe 2002). This technique was considered in this study.

3. Principal component analysis

The technique of PCA was first introduced by Karl Pearson in 1901. It is a descriptive technique to study the dependencies between variables, for a description or a compact representation of these variables. Since 70 years, many researchers have used the PCA method as a tool for processes modeling from which a model can be obtained (Kresta 1991, MacGregor 1995). It was also successfully applied as a technique for reducing the dimensionality of NN inputs in a variety of engineering applications (Harkat 2003, Kuniar and Waszczyszyn 2006, Shin 2008).

Mathematically PCA is an orthogonal projection technique that projects multidimensional observations represented in a subspace of dimension m (m is the number of observed variables) in a subspace of lower dimension ($L<m$) by maximizing the variance of the projections.

In practice, for modeling a process using PCA, the variables of this process are collected in a matrix X^b (m is the number of variables and N is the number of observations of each variable). X^b is given by

$$X^b = \begin{pmatrix} x_1(1) & x_2(1) & \dots & x_m(1) \\ x_1(2) & x_2(1) & \dots & x_m(2) \\ \vdots & \vdots & \vdots & \vdots \\ x_1(N) & x_2(N) & \dots & x_m(N) \end{pmatrix} \tag{1}$$

where, $x_1(1)$ represents the value of the first variable of the first observation. In order to make the result independent of the used units for each variable, a pre-treatment is necessary to focus and reduce the variables. Each column X_j of the new centered matrix is given by

$$X_j = \frac{X_j^b - M_j}{\sigma_j} \tag{2}$$

where, X_j^b is the j^{th} column of the matrix X^b and M_j its mean given by

$$M_j = \frac{1}{N}\sum_{k=1}^{N} x_j(k) \tag{3}$$

And, σ_j^2 its variance can be estimated using the Eq.

$$\sigma_j^2 = \frac{1}{N}\sum_{k=1}^{N}(x_j(k) - M_j)^2 \tag{4}$$

The new matrix of normalized data is noted

$$X = [X_1 \dots X_m] \tag{5}$$

The correlation matrix is given by

$$\sum = \frac{1}{N-1}X^T X \tag{6}$$

The estimation of PCA parameters can be summarized in the calculus of eigenvalues and eigenvectors of the correlation matrix Σ. From the spectral decomposition of this matrix it can be written as follows

$$\sum = P\Lambda P^T = \sum_{i=1}^{m} \lambda_i p_i p_i^T \tag{7}$$

Where, p_i is the i^{th} eigenvector of Σ and λ_i is the corresponding eigenvalue.

If there are q linear relationships between the columns of X matrix, we have q eigenvalues equal to zero, and the matrix X can be represented by the first L (m-q) principal components corresponding to eigenvalues not equal to zero. However, the eigenvalues equal to zero are rarely encountered in practice (quasi-linear relationship, noise...). So, it is necessary to determine the number L which represents the number of eigenvectors corresponding to the dominant eigenvalues. Many rules are proposed in the literature to determine the number of L components to retain (Valle 1999). In our study, the cumulative percentage of the total variance method was used. The basis of this method is to note that each principal component is representative of a portion of the variance of the process studied. The eigenvalues are the measure of the variance and can therefore be used in selecting the number of principal components. For the choice of L, the percentage of the total variance that needs to be kept should be chosen. The number of components is the smallest number taken so that this percentage is reached or exceeded; the components are successively selected in the order of decreasing variances. The percentage of variance explained by the first L components is given by

$$PCV(l) = 100\left(\frac{\sum_{i=1}^{l}\lambda_j}{\sum_{j=1}^{m}\lambda_j}\right)\% \tag{8}$$

4. Experimental database

The data of concrete mixes with Blast Furnace Slag (BFS), Fly Ash (FA) and Silica Fume (SF) as mineral additives in replacement to Cement (*C*) were extracted and collected form previous research projects and literature to build the database (Boukhatem 2011). Each set consists of concrete constituents and its corresponding workability and compressive strength. All the compressive strength values obtained using different types of specimens were generalized on (100×200 mm) cylinders cured under normal conditions. The slump was measured by the standard Abram cone slump test. The ranges and the limits of the constituents of concrete for each additive are shown in Tables 1, 2 and 3. Fig. 2 presents the distribution of the experimental data which was made according to the geographical origin of the additives by different researchers.

The following eight parameters were selected for slump models (cement (kg/m^3), additive (kg/m^3), fine aggregates (kg/m^3), coarse aggregates (kg/m^3), water (kg/m^3), superplasticizers (l/m^3), air entraining agent (ml/m^3) and temperature (°C). For compressive strength models, the same parameters were considered in addition to the age of testing (days). The data were organized according to six NN models as shown in Table 4. The data set was divided into 3 subsets: Training (60%), Testing (20%) and Validation (20%) for each model. The training set data was used to train the NN models, the entire validation data was used to stop the training process and all test data was used to assess the performance of the models after completion of the training process.

Table 1 Ranges of constituents and properties of concrete used

Components and properties		Data	
		Min	Max
Portland cement [ASTM Type I/CEMI/Type 10] (kg/m^3)		0	550
Additives (%)	Blast furnace slag (BFS)	10	80
	Fly ash (FA)	10	70
	Silica fume (SF)	05	20
Fine aggregates (FA) (kg/m^3)		400	960
Coarse aggregates (CA) (kg/m^3)		917	1385
Water (kg/m^3)		90	248
Admixtures	Super-plasticizer (l/m^3)	0	34
	Air entraining (ml/m^3)	0	1670
Water/Binder ratio		0.25	0.7
Temperature (°C)		5	50
Air quantity (%)		0.9	8
Age (days)		1	91
Compressive strength (MPa)		2	121
Slump (mm)		15	250

Table 2 Range of chemical compositions of the cement and the additives used

	SiO_2	Al_2O_3	Fe_2O_3	CaO	MgO	K_2O	Na_2O	SO_3	SSB (m^2/kg)
C	18.97-39	0.27-10	1.2-7.72	43-74.7	0.2-4	0.15-2.5	0.01-1.8	0.3-4.7	255-500
SBS	3.1-43.76	2.8-40	0.1-6.1	0.35-43	0.3-14	0.2-0.9	0.1-2.6	0.1-3.3	250-608
FA	23.1-93.8	0.06-35.4	0.09-28.9	0.12-36	0.16-13	0.3-4.2	0-7.3	0.1-5.1	211-930
SF	20.9-97.1	0.06-41	0.15-4.32	0.07-64	0-4.91	0.04-3	0-1	0.1-2.9	$12\text{-}54.10^4$

Table 3 Ranges of physical properties of aggregates, admixtures and specimens

Aggregates						Admixtures				Specimens	
Fine			Coarse			Superplasticizer		Air entraining			
FM	*D*	WA	Mx	*D*	WA	Base	*D*	Base	*D*	Type	Form (mm)
0.92 - 3.34	2.53 - 2.7	0.8 - 1.8	5-20 5-10	2.0 - 2.89	0.28 - 1.1	NSF	1.8-2.1	SR	1-1.17	Cube	100 and 150
										Cylindre	150×300, 100×200 and 160×320
										Prism	40×40×160 and 70×70×280

Note: FM: Fineness Modulus of Fine Aggregates, *D*: Density; Mx: Maximum size of Coarse Aggregates; WA: Water Absorption, NSF: Naphthalene Sulfonate Formaldehyde, SR: Synthetic Resin.

The components that form the input matrix of a NN model have different limits and are composed of correlated information with each other, so pre-processing and normalization of data are needed. In our context, the PCA method for the elimination of correlations between the parameters that compose the input matrix and also for reducing the problem size was applied. Then, the Min-Max boundary function on the uncorrelated data between -1 and 1 according to the limits of the used

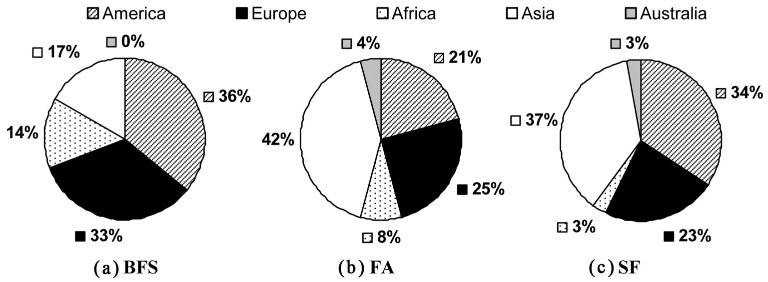


Fig. 2 Distribution of data according to the origin of the additive used

Table 4 The organisation of the database

Additive	Model identification	Training	Testing	Validation	Total
BFS	MPSBFS	101	33	33	167
	MPCSBFS	368	122	122	612
FA	MPSFA	66	21	21	108
	MPCSFA	240	80	80	400
SF	MPSSF	98	32	32	162
	MPCSSF	352	117	117	586

Note: *M*: Model; *P*: Predicting, *S*: Slump and CS: Compressive Strength.

Tang-Sigmoid activation function was applied. Finally, the BPMLP was allowed to act more effectively to find optimal models with improved generalization properties.

5. Methodology

This section describes the steps taken to implement the PCA and the NN approaches. The methodology is described in Fig. 3. Two types of PCA data processing were implemented in two phases. The first phase is called Pre-PCA, which is responsible for pre-processing the training data matrix concerning the concrete compositions, and eliminates correlations between them. The second is called Post-PCA, which is used to transform testing and validation data matrix according to its principal components. The implementation and simulation were performed using the MATLAB 7.5 functions of the Neural Networks toolbox (MATLAB 2007).

5.1 Pre-PCA phase

The use of the PCA function in MATLAB involves specifying a value corresponding to a desired value as a percentage of lower contribution of the input element. For example, a value of 0.05 means that the components that contribute less than 5% of the total variation in the data set will be rejected. From this point, this value will be simply referred as the Principal Component Variance (PCV).

Before using data (mixture proportions) of the input matrix to train a NN, they must be pre-

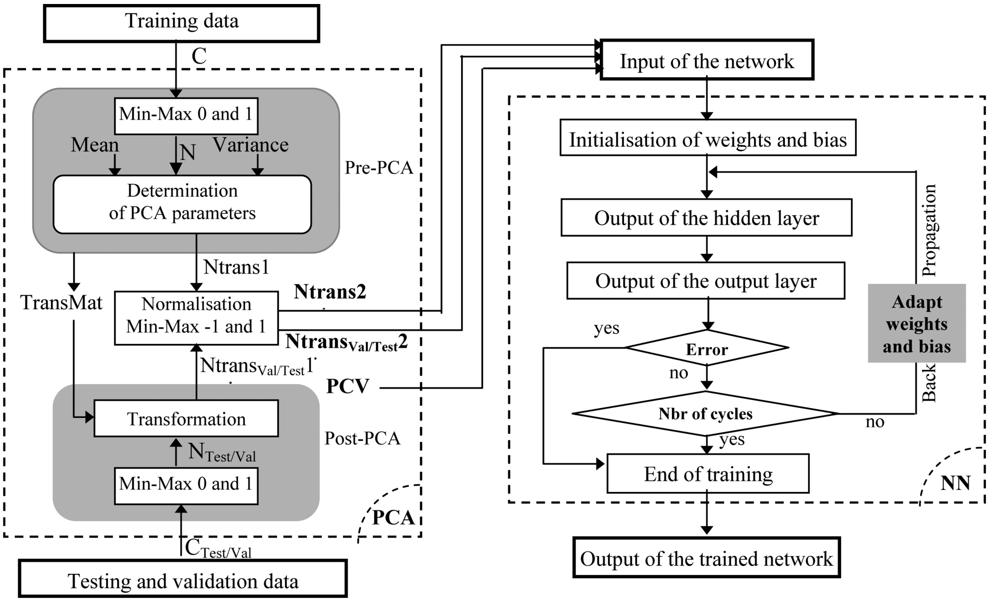


Fig. 3 Methodology of implementation of PCA and NN

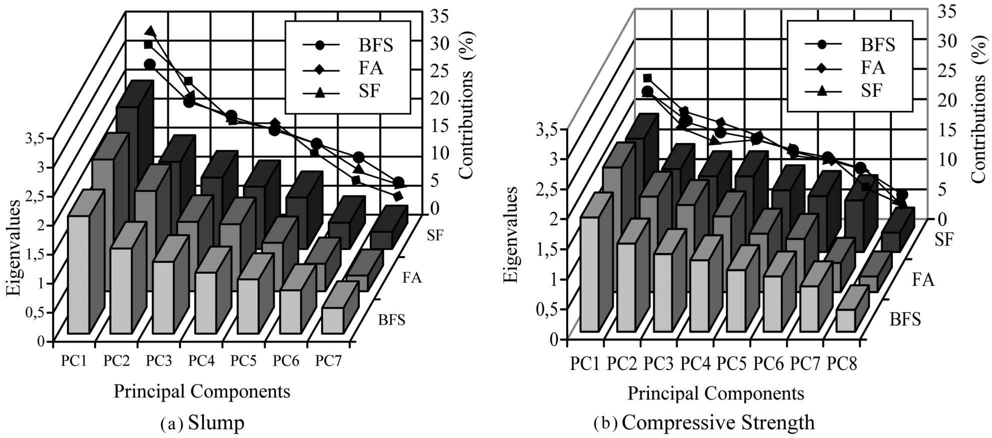


Fig. 4 Eigenvalues and contributions of components to the total variance

processed and normalized in order to extract the correlation between them (Fig. 3). First, data from the input matrix (C) were normalized, which means they have a mean of 0 and a variance of 1. Then, the PCA parameters (eigenvalues and eigenvectors) were estimated to calculate the principal components using the correlation matrix derived from the normalised data (N), the mean and variance values. After that, a transformation matrix is generated (TransMat) and a set of processed data (Ntrans) composed of non correlated orthogonal elements (principal components) is produced. These principal components were classified according to their variations.

Fig. 4 shows a representation of eigenvalues in terms of principal components for the six models and the relative contribution of each component to the total variance of data. For example, in the slag concrete slump model, the first component is about 25% of the variance; it means that this component represents a significant part on the slump. The components 2 and 3 are respectively

Table 5 Variances of the cumulative contributions of components

Components \ Models	Distribution of cumulative variances (%)					
	MPSBFS	MPSFA	MPSSF	MPCSBFS	MPCSFA	MPCSSF
PC1	25.33	28.46	30.58	21.11	22.98	20.93
PC2	43.72	50.13	49.36	37.45	40.57	36.23
PC3	59.21	65.11	64.79	51.81	56.66	50.16
PC4	72.31	79.60	78.22	65.03	70.58	64.17
PC5	83.95	90.04	89.30	76.41	81.36	75.52
PC6	93.26	95.97	95.01	86.64	91.18	85.79
PC7	98.83	99.32	98.71	95.06	96.58	95.34
PC8	-	-	-	99.09	99.41	98.92

Table 6 Variables importance according to components

Variables \ Models	Variables importance according to components (%)					
	MPSBFS	MPSFA	MPSSF	MPCSBFS	MPCSFA	MPCSSF
Cement	0.63(PC1)	0.51(PC2)	0.46(PC1)	-0.64(PC1)	0.63(PC3)	0.57 (PC1)
Additive	-0.52(PC1)	-0.55(PC4)	0.90(PC4)	0.55(PC1)	0.49(PC1)	-0.65(PC5)
Fine aggregates	-0.55(PC2)	-0.54(PC6)	-0.56(PC1)	-0.56(PC4)	-0.46(PC1)	-0.54(PC1)
Coarse aggregates	0.69(PC5)	0.61(PC3)	-0.51(PC3)	-0.51(PC5)	-0.55(PC7)	-0.60(PC3)
Superplasticizer	-0.65(PC4)	0.64(PC2)	-0.68(PC2)	0.46(PC3)	-0.61(PC4)	-0.55(PC2)
Air entraining	0.50(PC5)	-0.49(PC1)	0.76(PC5)	0.56(PC6)	0.59(PC7)	0.77(PC7)
Water	0.50(PC3)	-0.43(PC3)	0.54(PC2)	-0.60(PC2)	-0.71(PC2)	0.58(PC3)
Temperature	0.72(PC6)	0.81(PC5)	0.73(PC6)	0.69(PC7)	0.83(PC6)	0.67(PC5)
Age	-	-	-	0.78(PC5)	0.89(PC5)	0.88(PC6)

about 18% and 15% of the variance, while the last four components are approximately 13%, 12%, 9% and 6% respectively. The six components are about 93% of the total variance. The matrix TransMat was then stored for later use during the phase of Post-PCA.

The cumulative variances of the relative contribution of the principal components to the total variance of data for all models are given in Table 5.

Looking at the distribution values, the first principal components which have over 90% of the total variance of data were selected and the others were neglected, because they have no significant impact on the data. Thus, 8 and 9 parameters of the row input matrix can be replaced by 6 and 7 first principal components based on a chosen PCV values for slump and compressive strength models respectively. They were then introduced to the NN inputs with their desired output data. Many NN were trained using different PCV values to determine the optimal percentage of this value of the total variation in the database.

The PCA method allowed the determination of the significance of variables on the phenomenon to be studied (slump and compressive strength), where each variable is related to a component (Table 6). Thus, according to the order of these components the effect of each variable on slump and compressive strength can be classified. In our study some important findings concerning the effect of the components of concrete mixtures on the properties studied can be extracted. For example, for the MPSBFS we note that the first component refers primarily to cement and slag dosages. The second component is related to fine aggregates. The third component corresponds to water. The 4th, 5th and 6th correspond respectively to super-plasticizer, air entraining or coarse aggregates and temperature.

5.2 Post-PCA phase

During each training process of an NN, validation and generalization performance on testing and validation data sets were evaluated. Each vector of validation or test data must be post-processed with the Post-ACP before it can be used by an NN to estimate or predict the output (Fig. 3).

As in the pre-processing procedure, the validation of test data Cval/test were normalized (mean 0 and variance 1). Then, the normalized data, Nval/test were post-processed based on the correlation matrix TransMat (obtained during the pre-processing phase) to produce a new transformed data matrix, Ntransval/test composed of reduced and uncorrelated data. The new data, with its obtained optimal weights, was used for each trained network to predict designated concrete properties based on new concrete compositions and for all additives.

5.3 Training, testing and network selection

In this study, six NNs models have been developed (Table 4). Each model was trained and tested with their data set for training, testing and validation based on several values of PCV, using the Bayesian regularization algorithm (MacKay 1992). The reason to train more models is to get the best NN architecture, and the optimum PCV value. The best architecture means that the optimal number of hidden neurons must have an NN in the hidden layer and hence increases the NN generalization capacity. The optimum value of PCV determines the PC optimal number retained for each set of data and facilitates the NN training.

As mentioned previously, training, testing and validation of an NN were conducted simultaneously. In other words, after training an NN, the test and validation set data were presented to the network at each cycle to select the best NN. Therefore, the test and validation data were initially processed or normalised using the Post-PCA. After post-processing, a set of reduced and uncorrelated test data was produced and then integrated into the NN to get the output values for each test and validation set. This is based on calculating the sum of square errors which has a decreasing trend with the number of training cycles (iterations). It is given by the following expression

$$SSE = \sum_{i=1}^{N} (d_i - y_i)^2 \tag{9}$$

Where, SSE: the sum of square errors; d_i : the desired output; y_i : the real output of the model and N: the total number of data.

Then, once the desired errors have occurred, the output results obtained for each model were compared with the corresponding actual results. The comparison was made in terms of calculating the coefficient of determination R^2 and P value. Generally, the calculation of P value was used to justify the significance of the studied relation, because, even with a high coefficient of determination, if the P value is greater than 0.1, the relation is not significant. The relation is considered significant for P values less than 0.001. The ideal values of P and R^2 are 0 and 1 respectively.

6. Results and discussions

Table 7 summarizes the training performance and the different architectures adopted in this application. According to this table, the six models were applied by the introduction of the reduced and non-correlated data sets.

After achieving the training process, the models also provided the predictive slumps and compressive strength of concrete containing blast furnace slag, fly ash and silica fume according to concrete mixes data based on optimal PCV and best architectures. The best results were confirmed for the models with input vectors compressed by 6 and 7 PC for all the additives to predict concrete slumps and compressive strength respectively. The application of such models also led to a better prediction of the two designated properties. Finally, it was observed that beyond a determined PCV for all models (Fig. 5), the number of input components becomes smaller, generating a state of lack of information which prevents the models to be generalized. The overall results show that NN generalizes better with an optimal number of input data (PC) that does not consist of too much correlation between them.

Table 7 Architecture and parameters of the models developed

Additives	Input (*X*)	PCA Parameters			Architectures		NN Parameters				Output (*Y*)
		PCC	PCV	N.PC	N.HL	N.NHL	*Mu*	E/N.ITR	R^2	*P*	
BFS	8	93.26	0.06	6	2	10/12	0.005	0	1	10^{-4}	Slump (mm)
FA	8	95.97	0.06	6	2	5/5	0.005	0.004	0.98	0	
SF	8	95.02	0.04	6	2	5/9	0.005	0.01	0.96	10^{-6}	
BFS	9	95.06	0.03	7	2	7/20	0.005	0.006	0.96	0	Compressive strength (MPa)
FA	9	96.58	0.04	7	2	4/18	0.005	0.02	0.90	0	
SF	9	95.34	0.05	7	2	11/1	0.005	0.02	0.94	10^{-4}	

Note: N.HL: Number of hidden layers, N.NHL: Number of neurons in each hidden layer, *Mu*: adaptive mu value, N.ITR: Number of iterations or cycles, *E*: the error of the network; R^2: coefficient of determination and *P*: *P* Value.

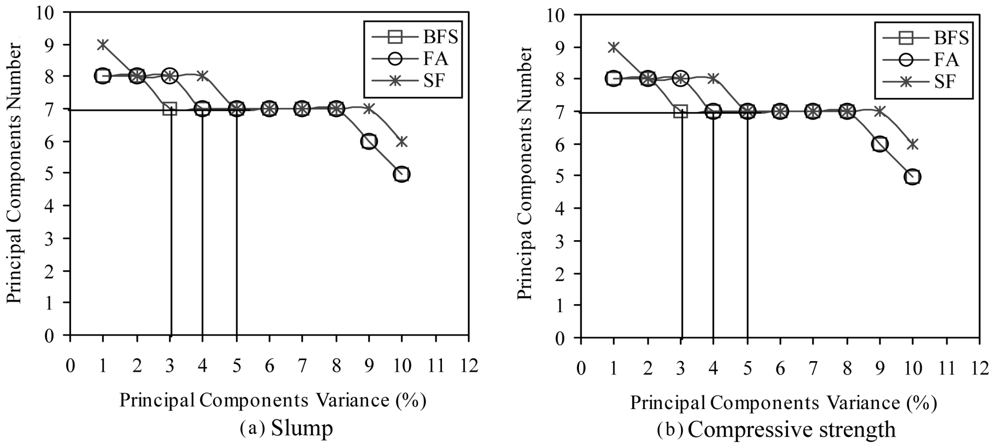


Fig. 5 Variation of principal components number with different PCV

7. Experimental program

To demonstrate the utility of the proposed method for improving the performance of the developed NN models, an experimental program was carried out. The completion of this program involved the collection of experimental results on the slump and the compressive strength at 3, 7, 28 and 91 days from different mixtures made of concrete at various water-binder ratios. We focused mainly on 3 types of ordinary concrete in which we replaced optimized quantities: 50% BFS, 25% FA and 10% SF by weight of cement of these supplementary cementing materials. High performance concretes was also made by replacing cement by weight with 30%, 15% and 10% BFS, FA and SF, respectively. The materials used in the experimental program were as follows:

1. Portland cement CSA Type GU from local areas in Canada;
2. Additives (blast furnace slag, fly ash class F and silica fume) from local areas in Canada;
3. Tap water;
4. Super-plasticizer: sodium Poly-Naphthalene Sulfonate (ASTM C 494 Type F), its relative density at 25°C is 1.21 and a solid content of 40.5%.
5. Air entraining: liquid hydrocarbons derived from water-soluble (ASTM C 260), its relative density at 25°C is 1.0 and a solid content of 5.0%.
6. Coarse aggregates: 80% of crushed stone 0-14 mm and 20% of the crushed stone 10-20 mm of

Table 8 Composition of concrete mixtures

Water/ Binder	Cement (kg/m^3)	Additives			Coarse aggregates (kg/m^3)		Fine aggregates (kg/m^3)	Admixtures		Water (kg/m^3)
		Type	%	Quantity (kg/m^3)	80% 5-14 mm	20% 10-20 mm		SP (%)	AE (ml/m^3)	
W/B=0.5	350	*C*	0	0	860	215	815	0	0	175
					856	214	694	0	350	
	175	BFS	50	175	910	228	737	0	0	175
					856	214	659	0	455	
	262.5	FA	25	87.5	912	228	738	0	0	175
					856	214	685	0	718	
	315	SF	10	35	915	228	741	0.7	0	175
					856	214	661	0.6	1200	
W/B=0.4	350	*C*	0	0	957	239	775	0.9	0	140
	175	BFS	50	175	955	238	773	1.1	0	140
	262.5	FA	25	84.5	950	237	769	0.6	0	140
	315	SF	10	35	957	239	775	1.2	0	140
W/B=0.3	500	*C*	0	0	1075		720	3.5	0	150
	350	BFS	30	150	1075		704	3.7	0	150
	425	FA	15	75	1075		695	3.3	0	150
	450	SF	10	50	1075		703	4.5	0	150
					1075		577	4	1603	

Note: For *W/B*=0.3 the maximum size of coarse aggregates varies from 2.5-10 mm, *C*: the control mixtures.

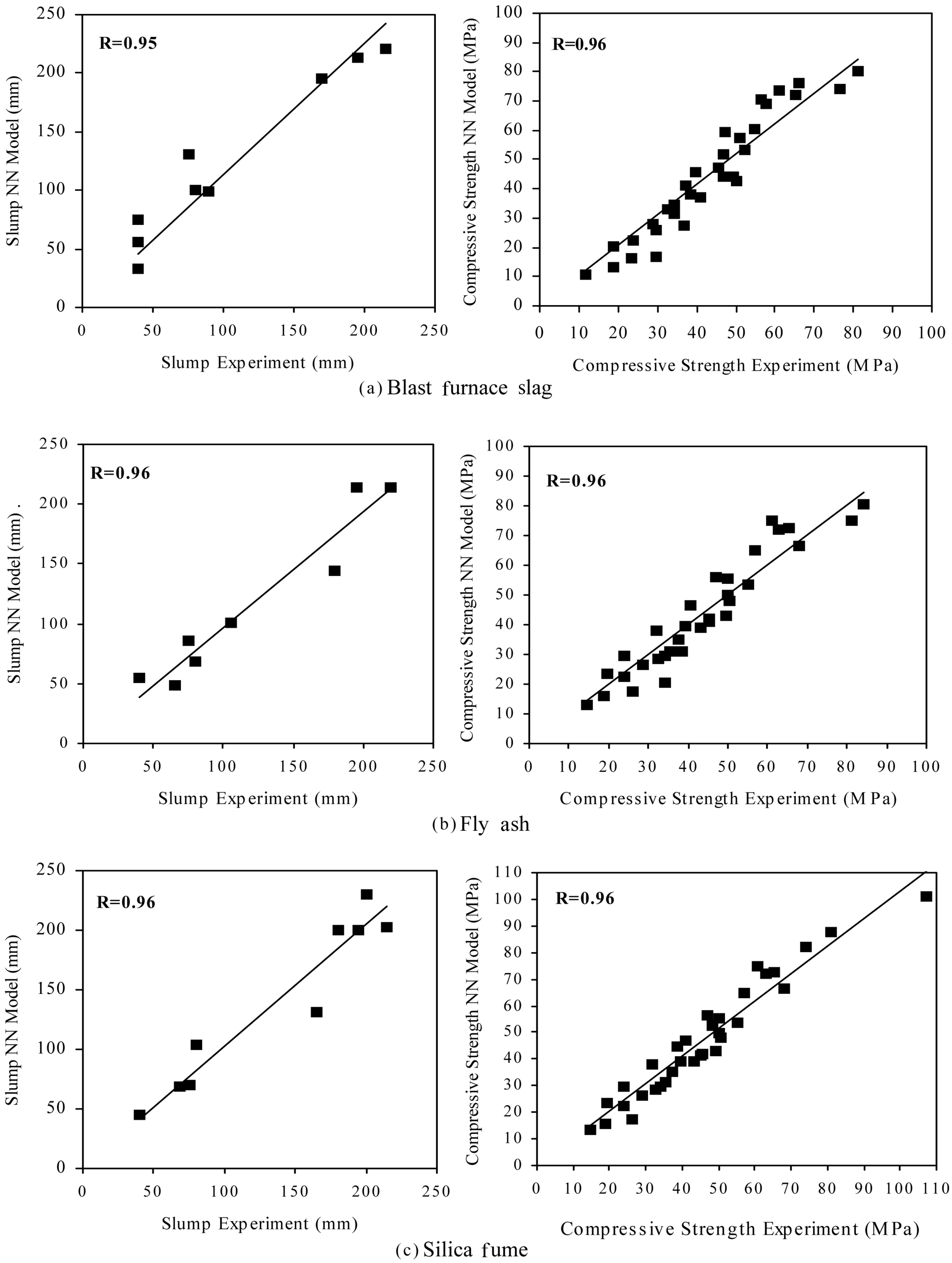
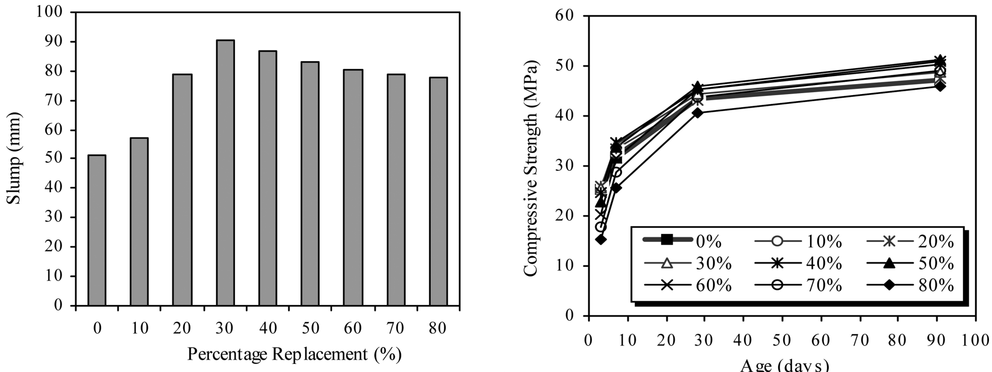


Fig. 6 Comparison of results models/experiments

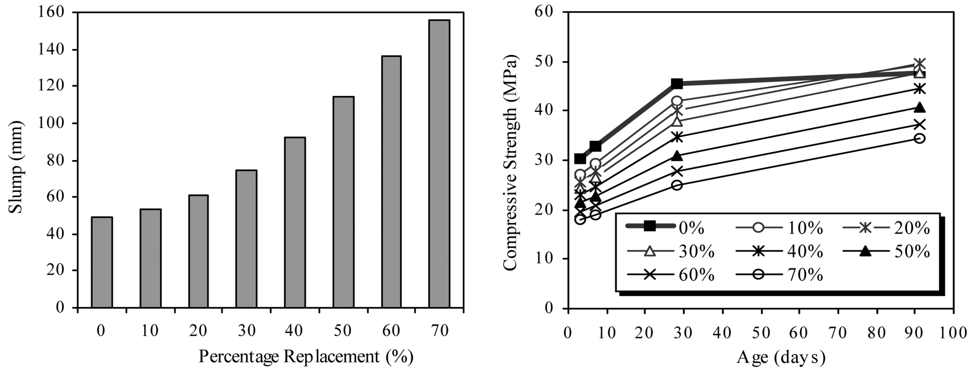
2.731 and 2.729 densities respectively (100% of crushed stone 2.5-10 mm of density 2.729 for high performance concrete).

7. Fine aggregates: Natural river sand with a module of fineness 2.6, water absorption of 1.16 and a density of 2653.

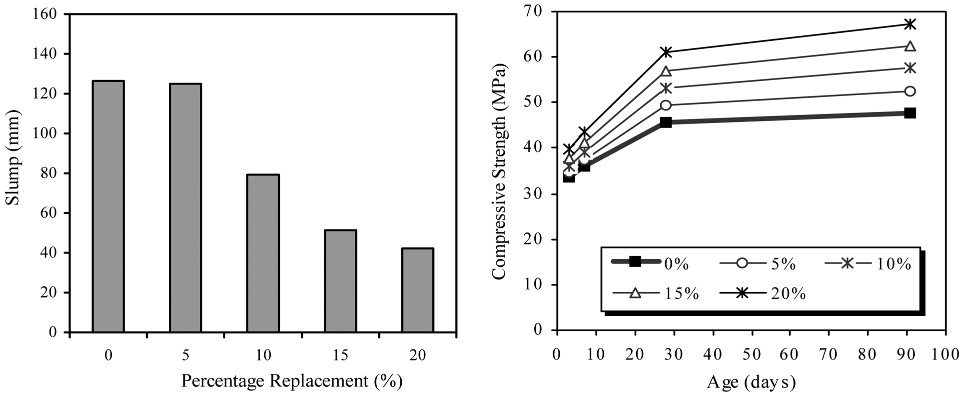
Table 8 presents the proportions of all the concrete mixtures used. The procedure used for the manufacture of mixtures is conforming to ASTM C 192 requirements. The workability of fresh concrete was evaluated using the slump test (ASTM C 143). Cylindrical specimens of 100×200 mm were made from 17 concrete mixtures. After 24 hours the specimens were demoulded and then kept in fog room of 100% relative humidity and a temperature of 20±3°C until the day of testing. The



(a) Blast furnace concrete



(b) Fly ash concrete



(c) Silica fume concrete

Fig. 7 Simulation results of slump and compressive strength compressive strengths were measured at 3, 7, 28 and 91 (ASTM C 93). Each compressive strength value is the average of three cylinders tests.

To demonstrate the prediction ability of the proposed methodology, the results of these "17 mixtures" were compared with those calculated by the developed models by introducing the same compositions of tested mixtures. Figs. 6(a)-(c) show clearly that there is a perfect correlation between the slumps and the compressive strength obtained experimentally and those predicted from the developed models.

8. Parametrical analysis based on the NNs results

The developed NN models can be used to simulate the effects of some parameters on the slump and the compressive strength of concrete. The analysis led to the following simulation results as shown in Fig. 7. This figure shows the large effect of the replacement level of slag, fly ash and silica fume on the slump and the compressive strength of the concrete mix which was produced based on the data listed in Table 9.

The results drawn from these curves are in conformity with concrete mix proportioning rules, found and accepted by researchers. To some extent, these reasonable results indicate that the developed NN models exhibit a good performance.

Table 9 Data of analysis for strength-age and slump curves

	Mix proportion			
Component	Mix 1 (control)	Mix 2 Slag (0-80%)	Mix 3 Fly ash (10-70%)	Mix 4 Silica fume (5-20%)
Water-to-binder ratio	0.5	0.5	0.5	0.5
Cement (kg/m^3)	350	350	350	350
Additives (kg/m^3)	0	(35-280)	(35-245)	(17-70)
Water (kg/m^3)	175	175	175	175
Superplasticizer (l/m^3)	0	0	0	1
Coarse aggregate (kg/m^3)	1075	1075	1075	1075
Fine aggregate (kg/m^3)	700	700	700	700

9. Conclusions

The application of neural networks approach for predicting concrete properties made it possible to develop systems with quite satisfactory accuracy. In order to improve the predictive ability of these systems, the principal component analysis approach was applied. The introduction of this technique led to the compression of the input data and the elimination of the correlations between them. For this reason, we combined these two approaches to predict effectively the slump and compressive strength of concrete containing mineral additives such as blast furnace slag, fly ash and silica fume. Two types of data processing were implemented in the MATLAB software environment for studying the effects of each parameter of the composition of concrete on the desired properties. Therefore, six models were developed. These models were validated by comparing their predicted results with experimental results of actual tests performed in the laboratory. The results suggest that applying PCA method for data processing is very useful for improving the prediction performance using the developed models. In addition to perfecting the generalization capacity of theses models, the PCA technique, also reduced the training time of the network due to the reduction of the dimension of input space especially in models involving a large number of input data.

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