PREDICTION OF STRENGTH OF HIGH PERFORMANCE CONCRETE USING NEURAL NETWORKS

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ABSTRACT

This paper presents the prediction of strength of high performance concrete using neural networks. Compressive strength and tensile strength of high performance concrete prepared with various wide ranges of combinations of by-product materials as cement replacing materials and various water-binder ratios are reported. A relationship between compressive strength and tensile strength of concrete is presented. Based on the experimentally obtained results, neural network has been used to establish its applicability for the prediction of compressive strength and tensile strength of high performance concrete. It was demonstrated that compressive strength of concrete can be predicted using neural networks.

Keywords: *Compressive strength; tensile strength, high performance concrete; neural networks*

الملخص

تقدم هذه الورقة طريقة للتنبؤ بقوة التحمل للخرسانة عالية الأداء باستخدام الشبكات العصبية كما تقدم الورقة نتائج قوى الضغط والشد للخرسانة عالية الأداء و التي تم تجهيزها باستخدام نسب مختلفة من الماء والمركبات الثانوية كبديل لجزء من الاسمنت. تعرض الورقة أيضاً العلاقة التي تم الحصول عليها بين قوة الشد والضغط للخرسانة عالية الأداء. بالإضافة لذلك فقد تم استخدام نتائج الأختبارات التي تم اجراؤها لمعرفة مدى دقة استخدام الشبكات العصبية للتنبؤ بقوة الضغط والشد للخرسانة عالية الأداء وقد تم التوصل الى انه يمكن استخدام الشبكات العصبية للتنبؤ بقوة الضغط للخرسانة.

1. INTRODUCTION

High-performance concrete (HPC) is relatively a new terminology used in the concrete construction industry. HPC is designed to give optimized performance characteristics for the given set of materials, usage and exposure conditions, consistent with requirements of cost, service life and durability. HPC should be determined in terms of both strength and durability performance under anticipated environmental conditions. Concrete having high strength does not necessarily imply that it will have long-service life. Concrete designed to have a special property for a particular application which a conventional concrete may not necessarily possess, is termed as high performance concrete. The ACI Committee (1993) defines HPC as, "Concrete meeting special performance requirements which cannot always be achieved routinely using any conventional constituents and normal mixing, placing and curing practices. These requirements may involve enhancements of the following: ease of placement without segregation, long-term mechanical properties, early-age strength, toughness, volume stability and life in severe environments". Therefore, high performance describes a concrete which is superior to ordinary concrete with respect to particular design properties because it has been tailored and optimized for every special application. HPC should have both high strength and high durability properties pertinent to an application.

Amongst all the engineering properties, strength is regarded as one of concrete's most important properties, although some other characteristics which are related to durability of concrete are gaining greater impetus. Strength gives an overall indication of the quality of concrete because the structure of cement paste is directly related to the strength.

It is now well established that in order to produce HPC a very dense homogeneous concrete microstructure especially in the interface region between hydrated paste and aggregate, is required [Mehta and Gjorv, 1982; Aitcin and Neville, 1993; Gjorv, 1994]. This is generally achieved through the use of low water-binder ratio between 0.20 and 0.30 with the help of superplasticizers that can produce slumps ranging from 70 to 130 mm. Additional densification and homogeneity of the interfacial region are achieved through the incorporation of mineral admixtures which improve concrete microstructure. Therefore, in addition to the three basic ingredients in conventional concrete, i.e., Portland cement, fine and coarse aggregates, and water, the making of HPC needs to incorporate supplementary cementitious materials, such as pulverised fuel ash (PFA), silica fume (SF) and/or blast furnace slag, and chemical admixture, such as superplasticizer.

Since the number of concrete ingredients incorporating supplementary admixtures needs to be considered in its design are more than those for ordinary concrete. It is difficult to predict the properties of this type of concrete using statistical empirical relationship. An alternative approach is to use neural networks. The neural networks approach is good for modeling nonlinear systems. A neural network model is a computer model whose architecture essentially mimics the learning capability of the human brain. The processing elements of a neural network, with many simple computational elements arranged in layers, are similar to the neurons in the brain.

Neural network applications used in this investigation are based on the radial basis function (RBF). A RBF neural network is a layered network consisting of an input layer, an output layer and at least one layer of nonlinear processing elements known as hidden layer. The input layer of the neural network receives signals from the external environment. The hidden layer receives signals from the input layer and transmits an output signal based on a transfer function to the subsequent layer.

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2. NONLINEAR MODELING

In this investigation, a nonlinear autoregressive model with exogenous inputs (NARX) [Leontaritis and Billings, 1985], which provides a concise representation for a wide class of nonlinear systems, is employed. The model is of the form as follows:

$$y(t) = f(y(t-1),\dots y(t-n_y), u(t-1),\dots u(t-n_u)) + e(t) \tag{1}$$

where: $y(t)$ is the output; $u(t)$ is the input and $e(t)$ accounts for any uncertainties; n_y, n_u are the maximum lags in the output and the input; $\{e(t)\}$ is assumed to be zero means white sequence; and $f(\,.\,)$ is some vector valued nonlinear function of $y(t)$ and $u(t)$, respectively. The present study employs an RBF network to model the input-output relationship. The nonlinear functional form $f(\,.\,)$ in the RBF expansion, used in this study is the Guassian function. The orthogonal least square (OLS) described by Chen *et al*. (1991), provides an elegant method for determination of model structure as well as parameter estimation.

2.1. Radial Basis Function

An RBF network can be regarded as a special two-layer network which is linear in the parameters provided all the RBF centres are prefixed. Given fixed centres i.e. no adjustable parameters the first layer or the hidden layer performs a fixed nonlinear transformation, which maps the input space onto a new space. The output layer then implements a linear combiner on this new space and the only adjustable parameters are the weights of this linear combiner. These parameters can therefore be determined using the linear least square method, which is an important advantage of this approach. A schematic of the RBF network with n inputs and a scalar output is shown in Fig. 1. Such a network could be represented as

$$\hat{y}(t) = w_0 + \sum_{i=1}^{n} w_i f\left(\|x(t) - c_i\|\right) \tag{2}$$

where: $\hat{y}(t)$ is the network predicted output; $x(t)$ is the network's input vector and presented as follows:

$$x(t) = [(y(t-1),\dots y(t-n_y), u(t-1),\dots u(t-n_u)]^T \tag{3}$$

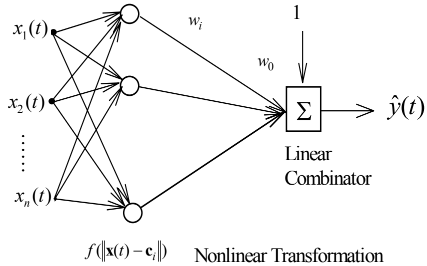

Fig. 1: Radial basis function network

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w_i are the weights or parameters; c_i are known as RBF centres and n_r is the number of centers or the hidden neurons. Once the functional form $f(.)$ and the centres c_i are fixed, and the set of input $x(t)$ and the corresponding desired output vector ($y(t)$ in this study) provided, the weights w_i can be determined using the linear least squares method.

Assuming the RBF network in Eq. (2) as a special case of the linear regression model is presented as follows:

$$y(t) = \sum_{i=1}^{M} p_i(t)\theta_i + \varepsilon(t) \tag{4}$$

where: $y(t)$ is the desired output; p_i are known regressors, which are some nonlinear functions of lagged outputs and inputs. That is

$$p_i(t) = p_i\big(x(t)\big) \tag{5}$$

with $x(t)$ defined in Eq. (3). A constant term (w_0 *in* Fig. 1) can be included in Eq. (4) by setting the corresponding term $p_i(t) = 1$. The residual $\varepsilon(t)$ is assumed to be uncorrelated with the regressors $p_i(t)$. It is clear that a given centre c_i with a given nonlinear function $f(\ .\ )$ corresponds to $p_i(t)$ in Eq. (4).

Eq. (4) for $t = 1,\ldots N$, can be written in the matrix form

$$y = P\Theta + E \tag{6}$$

the solution to find the parameter vector Θ, is given by the well known least squares (LS) method, provided the centres are fixed. However, orthogonal least squares (OLS) method proposed by Chen *et al.* (1991), yields both number of centres c_i, i.e. significant regressors as well as the corresponding parameter vector **Θ.**

3. EXPERIMENTAL PROGRAMME

Ordinary Portland cement (OPC) complying with BS12: 1991, PFA (complying with BS3892: Part 1: 1993) and SF were used throughout the investigation. The SF was obtained in slurry form with solids to water ratio of 50/50 by weight. A sulphonated naphthalene formaldehyde condensate superplasticizer was used to disperse the slurry. Fine aggregate (quarry sand) and coarse aggregate (uncrushed gravel) of 10 mm nominal size, were used. The fine aggregate was of medium grading in accordance with BS 882:1992. The aggregates were air-dried before use, and allowance was made for absorption when calculating batch weights. PFA and SF replacement levels were incorporated to make various binary and ternary cementitious combinations. Water-binder ratios (w/b) of 0.27, 0.40 and 0.50 were used. The slump for all the mixes investigated was maintained at 125±10 mm using the superplasticizer. The water contents of superplasticizer and SF slurry were taken into account when calculating the batch weights for mixing. In order to identify the specimen, ‘F’ and ‘S’ symbols were employed for

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PFA and SF, respectively. The numerical values after F and S represents the percentage of PFA and SF incorporated as cement replacement.

Cube compressive strength and splitting tensile strength measurements were carried out in accordance with BS 1881: 1983. Concrete 100 mm cubes were cast for compressive strength and cylinders of 100 mm diameter × 200 mm long were cast for the determination of splitting tensile strength. All the specimens were cast and compacted in accordance with BS 1881. After casting, the samples were covered under damp burlap and polyethylene sheets for 24 hours. The samples were demoulded the following day and then immediately kept in a mist room at 20±2^{o}C and 98±2% RH prior to testing.

4. RESULTS AND DISCUSSION

4.1. Compressive Strength

The change in compressive strength of concrete at various ages caused by the interactive effects of PFA and SF contents is demonstrated in Fig. 2. It can be seen that compressive strength decreased with an increase in PFA content for all ages investigated (Fig.2). At 7 days, SF affected the strength of PFA mixes and this seems to be related to the PFA content. An increase of strength is registered for PFA levels lower than 10% when SF is incorporated, however the results suggest that at higher PFA levels (>30%) the incorporation of SF results in a reduction in strength. At 28 days, up to 10% SF increased the strength for all levels of PFA replacements, whilst SF above 10% did not result in any advantage in improving the strength. At 90 and 180 days, only a modest improvement in strength has resulted from SF incorporation and this was evident for low levels of PFA (<10%) only.

The Influence of w/b ratio on compressive strength of concrete at various ages is shown in Fig. 3. From this figure it can be seen that the strength of concrete decreased with increasing w/b ratio for all ages, as to be expected. As curing age increases the reduction in strength with increasing PFA content becomes less apparent, especially for PFA contents <30%. As SF is incorporated at 10%, the overall level of strength is increased. The results also show that for >20% PFA content, the influence of the w/b ratio becomes more apparent when SF is not incorporated. The results indicate that early-age loss of strength of concrete as a result of incorporating PFA was compensated by the inclusion of SF to an extent depending on the quantity of PFA and SF.

4.2. Tensile Strength

The interactive effect of PFA and SF contents on the tensile strength of concrete is shown in Fig. 4. The incorporation of PFA decreased the tensile strength at all ages (Fig. 4). Up to 10% SF increased the tensile strength for all PFA replacement levels whilst incorporation of more than 10% SF did not show any advantage. An increase in SF content increased the

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tensile strength at 90 days whilst at 180 days SF inclusion did not exhibit significant influence on tensile strength.

The influence of w/b ratio on tensile strength of concrete at various ages is shown in Fig. 5. As expected, the tensile strength of concrete decreased with an increase in w/b ratio. There is a gradual decrease in tensile strength with an increase in w/b ratio. For a given w/b ratio, at 28 days tensile strength is significantly reduced as the PFA content is increased. However, as age increased, the reduction in tensile strength with increasing PFA content became less significant. The incorporation of 10% SF increased the overall tensile strength of concrete especially up to 90 days. It can be seen that >20% PFA content, the influence of w/b ratio was more significant when SF was not present.

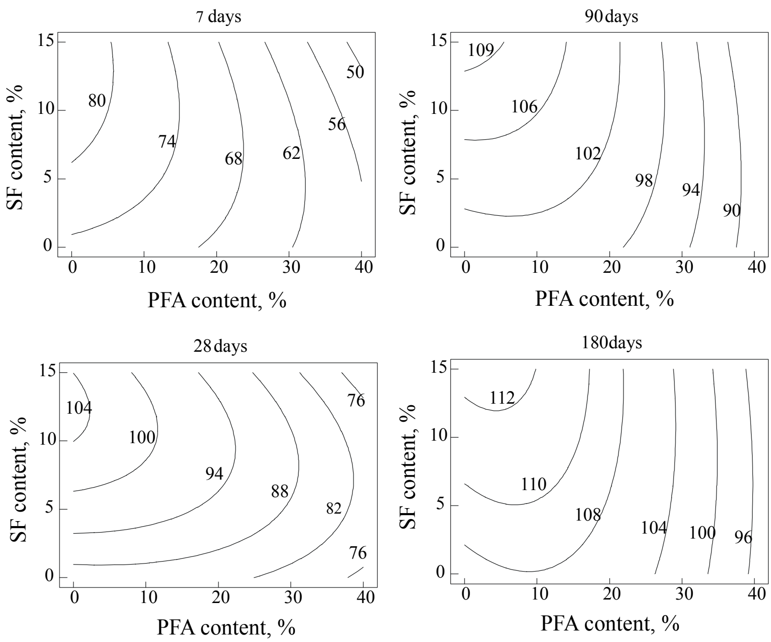

Fig. 2: Iso-compressive strength (MPa) of concrete at various ages, w/b ratio 0.27.

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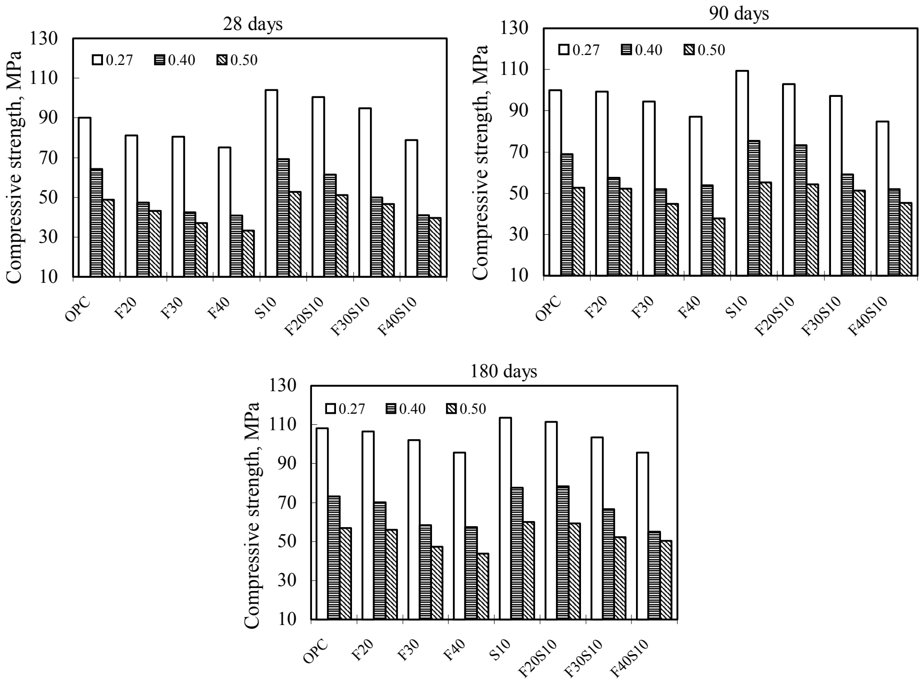

Fig. 3: Influence of w/b ratio on compressive strength of concrete at various ages.

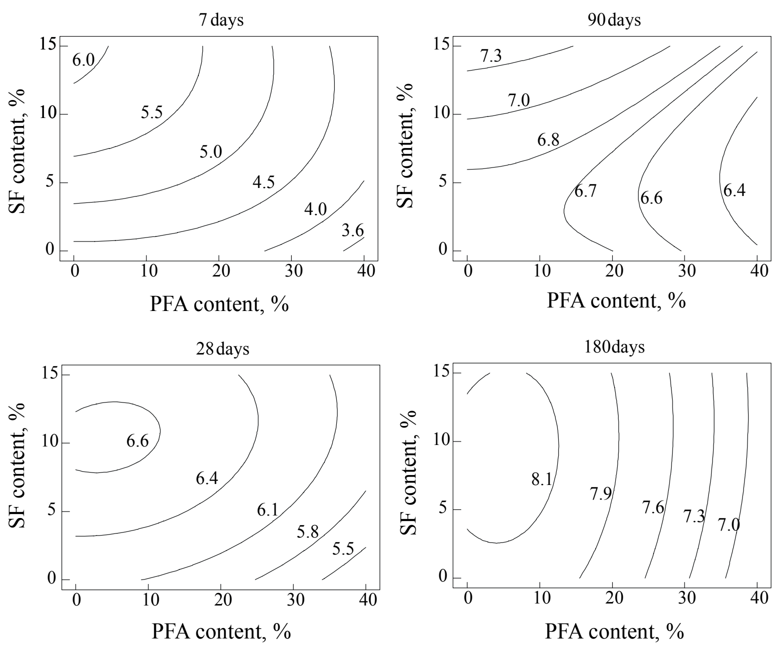

Fig. 4: Iso-tensile strength (MPa) of concrete at various ages, w/b ratio 0.27.

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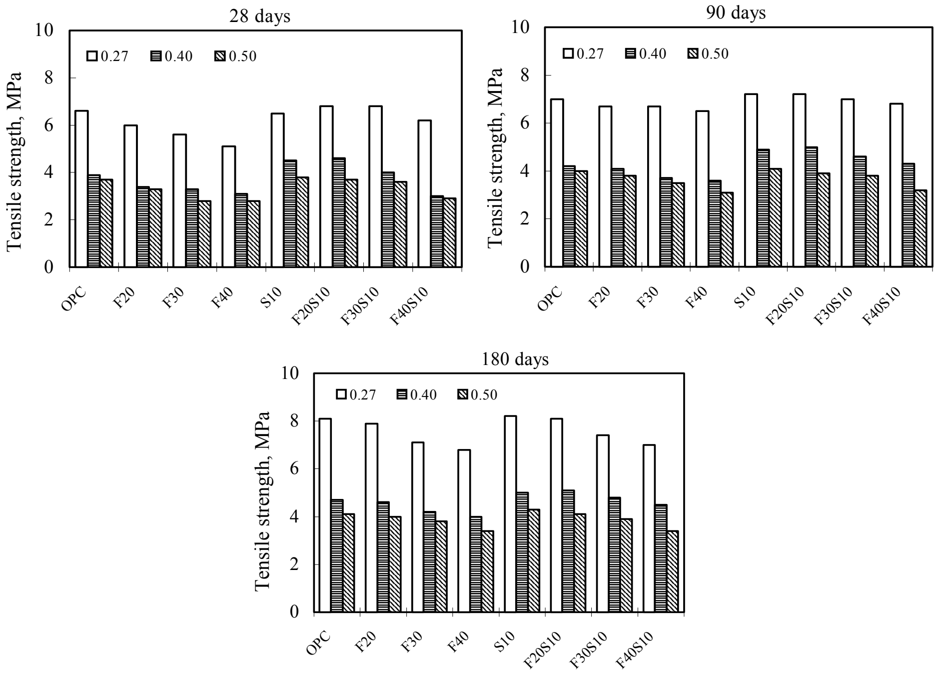

Fig. 5: Influence of w/b ratio on tensile strength of concrete at various ages.

4.3. Relationship Between Compressive And Tensile Strengths

The compressive strength of concrete is commonly considered in structural design but for some purposes the tensile strength is of interest for example in the design of highway and airfield slabs, shear strength and resistance to cracking [Neville, 1995]. A relationship between tensile strength and compressive strength exists but there is no direct proportionality and the ratio of the two strengths depends on the general level of strength of the concrete. In past, a number of empirical relationships between compressive strength and tensile strength have been suggested, many of them are presented in the following form:

$$f_t = kf_{cu}^a \tag{7}$$

where k and a are coefficients and the values of a have been suggested between 0.5 and 0.75. British Code of Practice BS 8007:1987 also suggests similar form of relationship and the values for k and a as 0.12 and 0.70 respectively. In this investigation the relationship between the compressive strength and the tensile strength was developed as shown in Fig. 6 and the equation is presented as follows:

$$f_t = 0.14 f_{cu}^{0.85} \; ; \qquad (R^2 = 0.95) \tag{8}$$

It is worth noting here that the above relationship (Eq. 7) is similar to that of Eq. 8, irrespective of presence of PFA and/or SF. It can be observed that the concrete mixes containing PFA and/or SF behave in a similar manner to that of OPC plain concrete. The detailed discussion on this topic is presented elsewhere [Khan and Lynsdale, 2002].

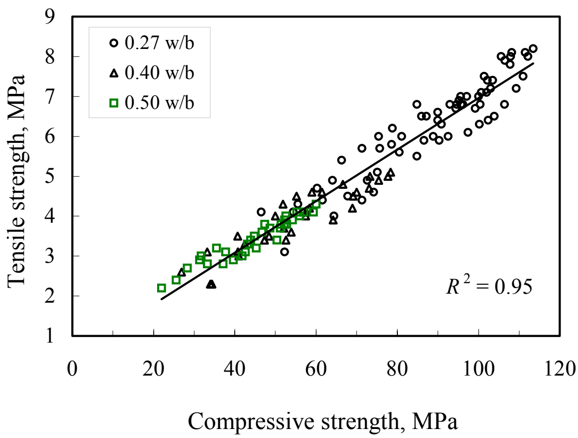

Fig. 6: Relationship between compressive strength and tensile strength of concrete.

5. NEURAL NETWORK SOLUTION

As mentioned above, this investigation RBF network was employed. The network developed in this investigation has eight units in the input layer and two units in the output layer. The experimentally obtained data have been divided into two sets, one for the network learning called learning set, and the other for testing the network called testing set. Each set is composed of dozens of pairs of input vectors and output vectors (vectors in the input layer called input vectors, and in the output layer called output vectors).

An input vector consists of 8 components which influence the output vectors (compressive strength and tensile strength) the most are as follows:

x_1 = OPC (kg/m^3); x_2 = PFA (kg/m^3); x_3 = SF (kg/m^3);

x_4 = Water (kg/m^3); x_5 = Superplasticizer (kg/m^3) x_6 = Fine agg. (kg/m^3);

x_7 = Coarse agg. (kg/m^3); x_8 = Age of testing (days).

The predicted values obtained using neural networks for compressive strength and tensile strength have been plotted against their respective experimentally obtained values as shown in Figs. 7 and 8, respectively. It can be seen from these figures that there is a good correlation between experimental values and those predicted using neural networks. Therefore, it is possible to predicted compressive strength and tensile strength of concrete using neural networks. It is interesting to note that the compressive strength represents a wide range of values from 30 to 115 MPa.

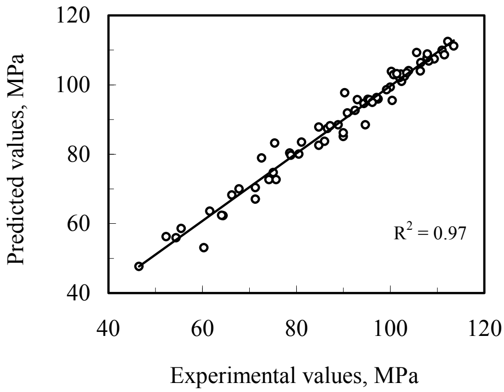

Fig. 7: Experimental values versus predicted values of compressive strength.

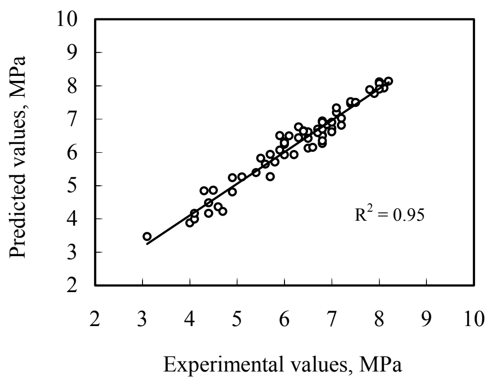

Fig. 8: Experimental values versus predicted values of tensile strength.

6. CONCLUSIONS

The incorporation of SF content increased the early-age strength for all mixes, compensating for the early-age strength loss as a result of PFA inclusion. It is worth noting that all the mixes were adjusted to equal workability by varying the amount of superplasticizer in each mix.

Concrete mixes containing 30% PFA and above with or without SF were not able to achieve the strength of OPC control. However, these systems are viable given the level of performance achieved when economical and environmental benefits are concerned.

Based on the experimentally obtained results, neural network has been used to establish its applicability for the prediction of concrete strength. It was demonstrated that strength of concrete can be predicted using neural networks.

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