Diyala Journal of Engineering Sciences

ISSN 1999-8716
Printed in Iraq

Second Engineering Scientific Conference
College of Engineering –University of Diyala
16-17 December. 2015, pp. 29-36

SUPPORT VECTOR MACHINE (SVM) FOR MODELLING THE STRENGTH OF LIGHTWEIGHT FOAMED CONCRETE

Suhad M. Abd, Abbas M. Abd,
Assistant Professor, Civil Engineering Department, College of Engineering, University of Diyala

ABSTRACT: In construction industry, strength is a primary criterion in selecting a concrete for a particular application. Concrete used for construction gains strength over a long period of time after pouring. The characteristic strength of concrete that considered in structural design is defined as the compressive strength of a sample that has been aged for 28 days. So rapid and reliable prediction for the strength of concrete would be of great significance. Prediction of concrete strength, therefore, has been an active area of research and a considerable number of studies have been carried out.

In this study, support vector machine model was proposed and developed for the prediction of concrete compressive strength at early age. The variables used in the prediction models were from the knowledge of the mix proportion elements and 7-day compressive strength.

The models provide good estimation of compressive strength and yielded good correlations with the data used in this study relative to nonlinear multivariable regression. Moreover, the SVM model proved to be significant tool in prediction compressive strength of lightweight foamed concretes with minimal mean square errors and standard deviation.

Keyword: Foamed Concrete, SVM.

1-INTRODUCTION

Concrete is considered worldwide as the most important building material and also the most common materials used in the construction of buildings or civil engineering structures.

Presently the construction industry has shown significant interest in the use of lightweight foamed concrete (LFC) as a building material due to its many favourable characteristics such as lighter weight, easy to fabricate, durable and cost effective[1].

Foamed concrete is a new generation of lightweight concrete that is versatile with some attractive characteristics such as its flowability, self-compacting and self-levelling nature, low dimensional change and ultra-low density. In addition, the material can be designed to have controlled low strength, excellent thermal insulation properties, and good load-bearing capacity and can be easily re-excavated, if necessary.

With its unique properties, foamed concrete has the potential to be used in various applications in the construction industry. For example, a study by Jones and McCarthy (2005) investigated the potential of foamed concrete for use as a structural material. Since foamed concrete has excellent thermal insulating properties and is lightweight, it can complement other materials to be used in higher strength structural applications [2].

It is well agreed in the literature review that constituent materials and mix proportions affect the properties and behaviour of foamed concrete. The possible effect of different constituent materials on the properties had been recognized from literatures and through past researches. The compressive strength of foamed concrete is affected by the density, cement type and content, water/cement ratio, surfactant type and curing regime [3].

Prediction methods for strength of concrete:

There are several strength prediction relations developed for plain cement paste, mortar and concrete [1,3]. Under the currently quicker pace of construction, there was a great need for more production of concrete with persisting on the conformability of the quality of the produced concrete with the standards and specifications. The compliance of any produced concrete with these specifications consider to be significant evidence for good concrete. Specifications usually specify test method as well as age of test. Strength of concrete, as specified by all the standards, is very important (from 1 to 28 days), because the early development of strength (early gain in strength) is very important. But, as early strength of concrete is important, strength at later ages is more important, because after all, it is this property which is relied upon in structural design of concrete as a construction material. The traditional 28 days standard test has been found to give general index of the overall quality (used in quality control process) and acceptance of concrete and has served well for so many years. Neither waiting for the result of such a test would serve the rapidity of construction, nor, neglecting it would serve the quality control process of the concrete. Moreover, rapid and reliable prediction of the results of 28 days strength test as early as possible would be of satisfaction for all parties instead of waiting for the traditional 28 days results [4].A number of improved prediction techniques have been proposed by including empirical or computational modelling, statistical techniques and artificial intelligence approaches.
Statistical techniques: A number of research efforts have concentrated on using multivariable regression models to improve the accuracy of predictions. Statistical models have the attraction that once fitted they can be used to perform predictions much more quickly than other modelling techniques and are correspondingly simpler to implement in software. This is especially true when comparing statistical modelling with artificial intelligence techniques. Statistical analysis can also provide insight into the key factors influencing 28 days compressive strength through correlation analysis. For these reasons statistical analysis was chosen to be technique for strength prediction of this study.

2-EXPERIMENTAL WORK

The materials that have been used in the experimental research program. Include the ordinary Portland cement (complies with the requirements specified in the British Standard BS EN 197-1: 2000), silica sand in different sizes (600 µm, 1.18 and 2 mm), water (normal tap water) and super plasticizers (GLENIUM) and foaming agent. Foamed concrete was produced and then poured in cubes. 150 sets of concrete cubes tested for their density and compressive strength at 7 and 28 days.

METHODOLOGY

Support Vector Machines (SVM)

Support Vector Machines (SVMs) are a powerful supervised learning algorithm used for classification or for regression. SVMs are a discriminative classifier: that is, they draw a boundary between clusters of data. Support Vector Machines are based on the concept of decision planes that define decision boundaries. A decision plane is one that separates between a set of objects having different class memberships. Support Vector Machine (SVM) is primarily a classier method that performs classification tasks by constructing hyper planes in a multidimensional space that separates cases of different class labels. SVM supports both regression and classification tasks and can handle multiple continuous and categorical variables [5]. For categorical variables a dummy variable is created with case values as either 0 or 1. Thus, a categorical dependent variable consisting of three levels, say (A, B, C), is represented by a set of three dummy variables:
A: {1 0 0}, B: {0 1 0}, C: {0 0 1}

To construct an optimal hyperplane, SVM employs an iterative training algorithm, which is used to minimize an error function. According to the form of the error function, SVM models can be classified into four distinct groups:

- Classification SVM Type 1 (also known as C-SVM classification)
- Classification SVM Type 2 (also known as nu-SVM classification)
- Regression SVM Type 1 (also known as epsilon-SVM regression)
- Regression SVM Type 2 (also known as nu-SVM regression)

Regression SVM

y = f(x) + noise

The task is then to find a functional form for f that can correctly predict new cases that the SVM has not been presented with before. This can be achieved by training the SVM model on a sample set, i.e., training set, a process that involves, like classification (see above), and the sequential optimization of an error function [5,6]. Depending on the definition of this error function, two types of SVM models can be recognized:

Regression SVM Type 1

For this type of SVM the error function is:

$$\frac{1}{2}w^T w + C\sum_{i=1}^{N}\xi_i + C\sum_{i=1}^{N}\xi^{\bullet}{}_i$$

which we minimize subject to:

$$w^T\phi(x_i) + b - y_i \leq \varepsilon + \xi_i^{\bullet}$$
$$y_i - w^T\phi(x_i) - b_i \leq \varepsilon + \xi_i$$
$$\xi_i, \xi_i^{\bullet} \geq 0, i = 1,\ldots, N$$

There are number of kernels that can be used in Support Vector Machines models. These include linear, polynomial, radial basis function (RBF) and sigmoid:

Kernel Functions

$$K(\mathbf{X}_i, \mathbf{X}_j) = \begin{cases} \mathbf{X}_i \cdot \mathbf{X}_j & \text{Linear} \\ (\gamma \mathbf{X}_i \cdot \mathbf{X}_j + \mathrm{C})^d & \text{Polynomial} \\ \exp(-\gamma \,|\, \mathbf{X}_i - \mathbf{X}_j \,|^2) & \text{RBF} \\ \tanh(\gamma \mathbf{X}_i \cdot \mathbf{X}_j + \mathrm{C}) & \text{Sigmoid} \end{cases}$$

Where $K(\mathbf{X}_i, \mathbf{X}_j) = \phi(\mathbf{X}_i) \bullet \phi(\mathbf{X}_j)$

That is, the kernel function, represents a dot product of input data points mapped into the higher dimensional feature space by transformation ϕ. Gamma is an adjustable parameter of certain kernel functions. The RBF is by far the most popular choice of kernel types used in Support Vector Machines. This is mainly because of their localized and finite responses across the entire range of the real x-axis.

Radial Basis Function (RBF)

It is a real-valued function whose value depends only on the distance from the origin, so that $\phi(X)=\phi(\|X\|)$; or alternatively on the distance from some other point c, called a center, so that $\phi(X,C)= \phi(\|X-C\|)$. Any function ϕ that satisfies the property $\phi(X) = \phi(\|X\|)$ is a radial function. The norm is usually Euclidean distance, although other distance functions are also possible. For example, using Lukaszyk–Karmowski metric, it is possible for some radial functions to avoid problems with ill conditioning of the matrix solved to determine coefficients wi, since the ‖X‖is always greater than zero.[7,8]

Sums of radial basis functions are typically used to approximate given functions. This approximation process can also be interpreted as a simple kind of network. Preethamet. al. 2014 presented the state of art of support vector mechanics method (SVM) problems related to civil engineering. Areas of many research are ongoing numerical investigations on SVM techniques are shown. Many researches from RBFs are also used as a kernel in support vector classification.[7]

3-RESULTS AND DISCUSSION

First: Traditional Multivariable Nonlinear Regression

To predict the 28^{th} day compressive strength of foamed concrete, the nonlinear regression was used and analyze adata set of 150 samples in this study. The main parameters controlled the properties of these samples was: density, cement content, sand content, w/c ratio, sand particle size, foaming agent, foam content, and the compressive strength at 7 and 28 day.The general model for the nonlinear regression for the compressive strength at 28 day was:

Var10=a0*v1^a1*v2^a2*v3^a3*v4^a4*v5^a5*v6^a6*v7^a7*v8^a8*v9^a9

Where:

Var10 (Dependent variable)= compressive strength at 28 day

V1 to V9 (Independent variables) =the input parameters

The Loss function used in this analysis was least squares.

When the actual observation compared with the predicted results using the developed model, the correlation coefficient was found R =0.97884248 and the r2 =0.9581326

The Level of confidence limit was: 95% (alpha=0.050). The coefficient of model parameters (a_n) was as listed in Table 1. Also this table show the standard deviation t-value and p-value for each one.

The actual observations plotted with the predicted results generated from the regression model in Figure 1(a). This plot explain the high correlation between the two data set and reflect the high accuracy of the developed model. There are few points around the compressive strength of 30 MPa was little diverge from the actual observations. This may belong to the properties of raw material and the specific condition of the samples tested.

Plotting the residual values with the predicted results reflect the good performance of the developed model. Again this plot shows exactly the amount of errors for each reading in term of predicted compressive strength. The interval around the 30 MPa is very clear here with some convergence from the actual observations, meanwhile the most results was of error ranging between (-4 to +4) as shown in Figure 1(b).The overall correlation coefficient for the 9-inputs and the target output shows that the highest correlations with the 28^{th} day compressive strength was with the 7^{th} day compressive strength, density, and cement content respectively in positive direction. It was correlated in negative direction with w/c ration, sand/cement ration and foam content respectively.

Second: Super Vector Machine

To implement this technique, the compressive strength at 28^{th} day considered as the dependent variable (Var10), and the other inputs (V1 to V9) as the independent variables. The sample size of 150 overall observations was randomly divided into Train of (111 samples), and Test of (39 samples. The support vector machine of type 1 was adopted for the analysis process. The four Kernel function types were tested: Radial Basis Function, linear, polynomial, and sigmoid. This process results were listed in Table 2.

It was clear that the RBF has the best results in term of highest correlation for train, test and overall data set. It has the minimum mean square error amongst the four functions, and have the minimal standard deviation. So the detailed discussion will focus on the RBF to explain the main features of this model. Table 3 illustrates that the total error mean in the predicted model was found around (-0.32084) for all investigated samples. The overall correlation coefficient was around (99%) and this value considered very high and reflect the greet degree of precision of the developed model.

Also Figure2 plots the observed data set against predicted values of the RBF for the train, test and overall data set. It is very clear that the predicted points distributed very close to the equality line. For each data set the formula for the best fitting was provided with its plot.

CONCLUSIONS

A mathematical model for the prediction of the lightweight foamed concrete compressive strength was proposed in this study. The technique used to perform the proposed model was traditional multivariable nonlinear regression and revolutionary Support Vector Machine modelling. The results revealed excellent correlation between the observed and predicted values for the data set used in this study. Both techniques proved to be attractive tool for the prediction process. The SVM that adopted radial base function characterized with minimum mean square error relative to other functions and the traditional regression. Also this method has the minimal standard deviation for the predicted results compared with other techniques. This reflect the high precision of this tool along all points in the predicted results for the data set beside the overall correlation.

REFERENCES

[1]. MdAzree Othuman Mydin. 2011. Potential of Using Lightweight Foamed Concrete in Composite Load-Bearing Wall Panels in Low-Rise Construction, Concrete research letters, Vol. 2 (2).Pp 213-227.

[2]. Jones, M.R. & McCarthy, A. 2005. Preliminary views on the potential of foamed concrete as a structural material. Magazine of Concrete Research 57(1): Pp:21-31

[3]. Suhad M. Abd, MFM Zain, Roszilah Hamid and Abbas M. Abd. 2008. Fuzzy Modelling System to Predict the Compressive Strength of Concrete. Proc. of national seminar on Fuzzy theory and fuzzy: from theory to applications, UiTM University, Malaysia. Pp:1-16.

[4]. Kheder, G. F. , A. M. Al Gabban and S. M. Abid. 2003. Mathematical model for the prediction of cement compressive strength at the ages of 7 and 28 days within 24 hours. Material and structure. Vol. 36, December 2003, Pp 693-701.

[5]. O. Chapelle, V. Vapnik, O. Bousquet, and S. Mukherjee, "Choosing multiple parameters for support vector machines," Machine Learning, vol. 46, pp. 131-159, 2002.

[6]. Lukaszyk, S. (2004). A new concept of probability metric and its applications in approximation of scattered data sets. Computational Mechanics, V(33), pp:299-3004.

[7]. Preetham. S, Shivaraj. M, W. P. Prema kumar3 and H. Ravi Kumar. 2014. Support vector machines technique in analysis of Concrete- critical review. International Journal of Emerging Technologies and Engineering (IJETE). V 1, issue 9. Pp 199-203.

[8]. Abbas M Abd, and Suhad M Abd. 2014. Neuro-Fuzzy Model to Evaluate Ready-Mix Concrete Properties. IJERST, Vol 3 (1), Pp 24-33.

Table 1: The coefficient of regression model (parameters a).

parameter	variable	Estimate	Standard - error	t-value - df = 140	p-value
a0		0.000041	0	0.33857	0.735442
a1	density	1.13292	0.58	1.9684	0.050997
a2	cement	0.33708	61506.59	0.00001	0.999996
a3	sand	0.338127	61506.55	0.00001	0.999996
a4	sand/cement	-0.1796	61506.57	0	0.999998
a5	water/cement	0.328483	0.15	2.24687	0.026213
a6	sand-size	-0.21411	0.03	-7.50364	0
a7	Agent	-0.07656	0.02	-3.81834	0.000201
a8	foam	0.107572	0.06	1.72006	0.087631
a9	comp-7D	0.5375	0.05	11.1801	0

Table 2: Support Vector machine the four type functions results

Function Type	Correlation coefficient	Mean square error	Standard deviation
Radial Basis Function	0.986(Train), 0.990(Test), 0.987(Overall	3.880(Train), 3.268(Test), 3.721(Overall)	0.170(Train), 0.147(Test), 0.165(Overall)
linear	0.951(Train), 0.945(Test), 0.949(Overall)	18.444(Train), 25.263(Test), 20.217(Overall)	0.369(Train), 0.413(Test), 0.381(Overall)
polynomial	0.976(Train), 0.986(Test), 0.978(Overall)	6.714(Train), 5.357(Test), 6.361(Overall)	0.225(Train), 0.178(Test), 0.215(Overall)
sigmoid	0.851(Train), 0.877(Test), 0.859(Overall)	67.969(Train), 66.761(Test), 67.655(Overall)	0.716(Train), 0.673(Test), 0.703(Overall)

Table 3. Main features of the RBF support vector machine model

Number of support vectors	30 (16 bounded), (gamma=0.111)
model specifications (decision constants)	0.124238
Observed mean	26.90346
Predictions mean	27.22430
Observed S.D.	12.28756
Predictions S.D.	11.54473
Mean squared error	3.26776
Error mean	-0.32084
Error S.D.	1.80225
Abs. error mean	1.49713
S.D. ratio	0.14667
Correlation	0.99

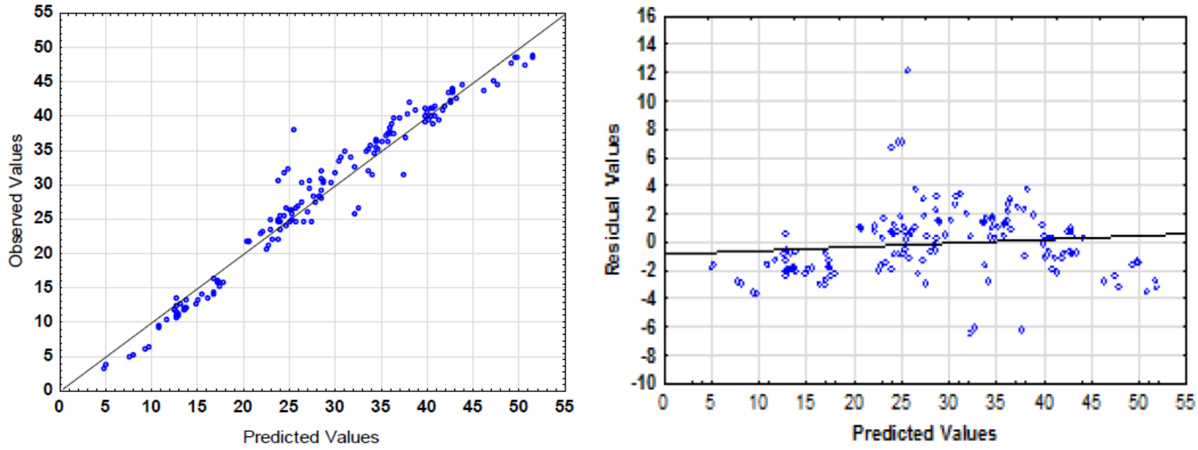
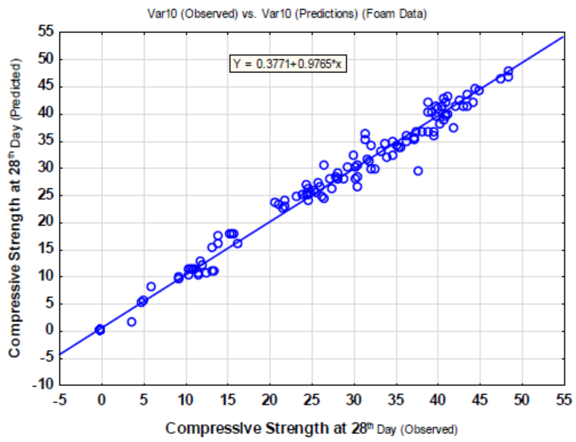
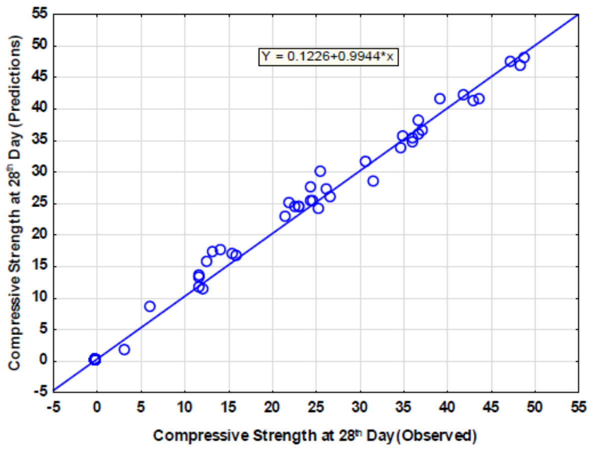


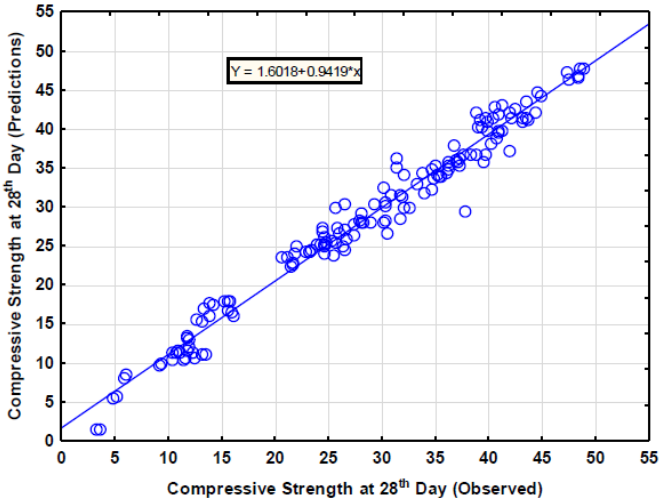
Figure 1. (a) Observed vs. predicted, (b) residual vs. predicted results



(a) Train data set



(b) Test data set



(c)Overall data set

Figure 2. Correlation plot for (a) train data, (b) test data, and (c) Overall data set

اعتماد تقنية (SVM) للتنبؤ المبكر بمقاومة الخرسانة الرغوية خفيفة الوزن

ا.م.د سهاد محمد عبد ، ا.م.د عباس مهدي عبد
قسم الهندسة المدنية / كلية الهندسة / جامعة ديالى

الخلاصة:

تعتبر مقاومة الانضغاط هي العامل الرئيسي المحدد للتطبيقات الممكنة للخرسانة في القطاع الانشائي، حيث تكتسب الخرسانة قوتها وفق دالة زمنية طويلة بعد عملية الخلط والصب. ولان المقاومة الاسمية هي العنصر المعتمد في التصميم الانشائي كونها مقاومة الخرسانة بعمة 28 يوما. لذا فان امكانية التنبؤ المبكر بمقاومة الخرسانة سيكون ذا اهمية قصوى وعليه فقد اجريت العديد من الدراسات لهذا الموضوع عالميا.

في هذا البحث، تم اعتماد تقنية (SVM) للنمذجة الرياضية لتطوير نموذج رياضي يمكن من التنبؤ بمقاومة انضغاط الخرسانة بعمر مبكر. وتم اعتماد مجموعة من العوامل المؤثرة في خواص الخرسانة الرغوية كمدخلات للنموذج الرياضي، وتمثل العناصر الرئيسية للخلطة الخرسانية.

بينت النتائج ان النموذج المعتمد قد وفر تخمينا مبكرا لمقاومة الانضغاط للخرسانة الرغوية باعتماد فحص الانضغاط بعمر سبعة ايام مع مكونات الخلطة الخرسانية كمدخلات. كان معامل الارتباط عاليا عند مقارنة المشاهدات الفعلية مع البيانات التنبؤية للنموذج الرياضي. وتفوق هذا النموذج على تقنية الانحدار اللاخطي المتعدد من حيث مؤشرات معدل مربع الفروقات والانحراف المعياري. بينت النتائج امكانية اعتماد هذا النموذج الرياضي بشكل موثوق وفعال وفق نطاق البحث.