Paper 71

©Civil-Comp Press, 2012
Proceedings of the Eighth International Conference
on Engineering Computational Technology,
B.H.V. Topping, (Editor),
Civil-Comp Press, Stirlingshire, Scotland

Support Vector Machine Modelling for the Compressive Strength of Concrete

A. Sriraam[1], S.K. Sekar[2] and P. Samui[2]
[1]School of Mechanical and Building Sciences
[2]Centre for Disaster Mitigation and Management
VIT University, Vellore, India

Abstract

Concrete is the primary building component used ubiquitously for a long time. The scarcity of river sand, one of the constituent materials used in the production of conventional concrete, was reported in India. This article employs support vector machines for analysing the feasibility of utilising granite fines as a substitute for natural river-bed sand in concrete, a material that complements sand reducing the construction cost. Mix design was developed for M20 grade concrete using the IS: 10262 (2009) code design. Results show the use of support vector machines based models to effectively predict the outcome of the compressive strength of concrete. Observation validates 35% granite fines content as optimum for augmented structural performance.

Keywords: granite powder, compressive strength, concrete, fine aggregate, riverbed sand, support vector machines.

1 Introduction

Concrete is a manufactured conglomerate stone made essentially of Portland cement, water, sand and coarse aggregates. The water reacts with the cement, hence bonding the other components together. This eventually creates a robust stone-like material concrete having high compressive strength in comparison to its low tensile strength. Therefore, concrete is usually reinforced with materials that are strong in tension. Concrete, used in rigid constructions, has an unusually high cost which arises from the market price of its constituent materials. Such costs can be reduced through domestically available materials or alternatives to the conventional constituents. As said earlier, sand is a major component of concrete and without which, concrete will not fulfil its purpose. Sand is usually a larger component of the mix than cement.

There are many developing nations around the world today leading to high consumption of sand as fine aggregate in concrete production. Due to which several undeveloped and developing nations have encountered hindrance in their regular supply of natural river sand preventing infrastructural development. The scarcity of sand and the resultant escalation in its price have put the brakes on the construction industry in India. Sand, which was available at a cost of Rs. 22 per cubic feet (c.ft) a year ago, now costs Rs. 50 per c.ft and Rs. 10,000 per lorry load (200 c.ft). India's Public Works Department (PWD) estimated in 2001 that sand deposits especially in Tamil Nadu Rivers would meet the construction demand only for 25 years. Since then, the real estate and IT boom have resulted in manifold increase in construction activity. Tamil Nadu state now requires about 20,000 to 25,000 truckloads of sand per day. Recently, Tamil-Nadu government (India) has imposed restrictions on sand removal from the river beds due to unsafe impacts threatening many parts of the state.

To overcome the stress and demand for river sand, researchers and practitioners in the construction industries have identified some alternative namely quarry dust, and M-sand. In India, the use of quarry dust to replace river sand was reported by Ilangovan R and Nagamani K in 2007 [1]. The use of rock dust as an alternative to natural sand was also studied by Nagaraj TS and Banu Z in 1996 [2]. The use of up to 20% quarry waste fine as a partial replacement for natural sand in the production of concrete, in Malaysia was also researched by Safiuddin MD et al. in 2007 [3]. Use of crushed granite fines or crushed rock fines as an alternative to sand in concrete production was also studied by Murdock L.J et al. in 1991 [4]. On the other hand, the granite waste generated by the industry has accumulated over years. Insignificant quantities have been utilised and the rest were dumped unscrupulously resulting in environment problem. With the enormous increase in the quantity of waste needing disposal, acute shortage of dumping sites, sharp increase in the transportation and dumping costs affecting the environment, prevents the sustainable development. Our objective of this article is aimed at developing a new building material from the granite scrap, an industrial waste, as a replacement material of fine aggregate in concrete. By doing so, intentional reduction of cost of construction can be studied along with the increased strength of concrete. This will help to overcome the problem associated with its disposal including the environmental problems of the region.

Concrete mixes are designed based on standardised international codes and recommendations or quondam experiences only. Experimental and human errors in mix designs and making of concrete are events that vary the compressive strength substantially. Re-designing the concrete mix proves costly and time consuming. Thus, advanced statistical methods estimate the compressive strength of concrete based on its constituents at the time of design. Prediction of concrete compressive strength is important in the construction domain as it postulates the time required for removing concrete form, project scheduling and quality control. This paper adopts support vector machines for determination of compressive strength of concrete through the replacement of sand by granite fines.

2 Support Vector Machines

Support vector machines (SVM) is a powerful machine learning method for both regression and classification problems. Within a short period of time, Scholkopf stated that SV classifiers became competitive with the best available systems in 1997 [5]. However, the various SVM formulations each require the user to set two or more parameters which govern the training process, and those parameter settings can have a profound effect on the resulting engine's performance. SVM has originated from the concept of statistical learning theory pioneered by Boser et al. in 1992 [6]. This article uses the SVM as a regression technique by introducing a ε-insensitive loss function. In this section, a brief introduction on how to construct SVM for regression problem is presented. More details can be found in many publications (Boser et al. 1992 [6]; Cortes and Vapnik 1995 [7]; Vapnik 1998 [8]). There are three distinct characteristics when SVM is used to estimate the regression function. First of all, SVM estimates the regression using a set of linear functions that are defined in a high dimensional space. Secondly, SVM carries out the regression estimation by risk minimisation where the risk is measured using Vapnik's ε-insensitive loss function [8]. Thirdly, SVM uses a risk function consisting of the empirical error and a regularisation term which is derived from the structural risk minimisation (SRM) principle.

Considering a set of training data $\{(x_1, y_1),...,(x_n, y_n)\}, x \in R, y \in r$. Where x is the input, y is the output, R^N is the N-dimensional vector space and r is the one-dimensional vector space. The input variable used for the SVM model in this study is the percentage of granite fines, and compressive strength of concrete $\left[f_c^{'}\right]$ is the output of the SVM model. Therefore, $x = [\%GF]$ and $y = \left[f_c^{'}\right]$. The ε-insensitive loss function can be described in the following way

$$L_{å}(y) = 0 \text{ for } |f(x) - y| \le å \tag{1}$$

Otherwise $L_{å}(y) = |f(x) - y| - å$

Figure 1. defines an ε tube, and when the predicted value is within the tube, the loss is zero. Meanwhile, if the predicted point is outside the tube, the loss is equal to the absolute value of the deviation minus ε. The main aim in SVM is to find a function $f(x)$ that gives a deviation of ε from the actual output and at the same time is as flat as possible. Let us assume a linear function

$$f(x) = (w, x) + b, w \in R^N, b \in r \tag{2}$$

Where, w is an adjustable weight vector and the scalar threshold b. In equation (2), a smaller w is attained for flatness.

One way of obtaining this is by minimising the Euclidean norm $\|w\|^2$. This is equivalent to the following convex optimisation problem.

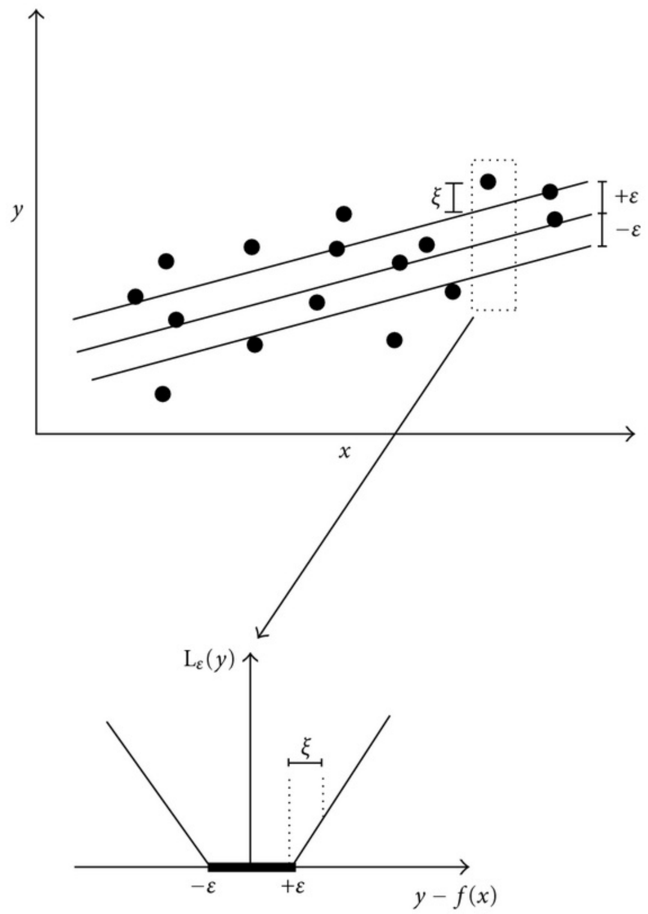

Figure 1: Pre-specified Accuracy ε and Slack Variable ξ in support vector regression [Scholkopf (1997)]

Minimise: $\frac{1}{2}\|w\|^2$ (3)

Subjected to: $y_i - \left(\langle w.x_i \rangle + b\right) \leq \mathring{a}$, i = 1, 2, ..., n

$\left(\langle w.x_i \rangle + b\right) - y_i \leq \mathring{a}$, i = 1, 2, ..., n

The above convex optimisation problem is feasible. Sometimes, in certain situations, allowing for some errors bear out economically feasible for the case of granite fines as a replacement for sand. As shown in the Figure 1, the parameters $\hat{\imath}_i, \hat{\imath}_i^*$ are slack variables that determine the degree to which samples with error more than ε be neglected. In other words, any error smaller than ε does not require $\hat{\imath}_i, \hat{\imath}_i^*$ and hence does not enter the objective function because these data points have a value of zero for the loss function. The slack variables ($\hat{\imath}_i, \hat{\imath}_i^*$) are introduced to avoid infeasible constraints of the optimisation problem shown in equation (4).

Minimise: $\frac{1}{2}\|w\|^2 + C\sum_{i=1}^{n}\left(\hat{\imath}_i + \hat{\imath}_i^*\right)$ (4)

Subjected to: $y_i - \left(\langle w.x_i \rangle + b \right) \leq \mathring{a} + \hat{\imath}_i$, i = 1, 2, ..., n

$\left(\langle w.x_i \rangle + b \right) - y_i \leq \mathring{a} + \hat{\imath}_i^*$, i = 1, 2, ..., n

$\hat{\imath}_i \geq 0$ and $\hat{\imath}_i^* \geq 0$, i = 1, 2, ..., n

The constant 0 < C < ∞ determines the trade-off between the flatness of f and Smola and Scholkopf suggested the amount up to which deviations larger than ε can be tolerated in 1996 [10]. This optimisation problem given in equation (4) is solved by Lagrangian Multipliers (Vapnik, 1998), and its solution is given by

$$f(x) = \sum_{i=1}^{N} \left(\alpha_i - \alpha_i^* \right) K\left(x_i, x_j \right) + b \qquad (5)$$

Where b, α_i, α_i^* are the Lagrangian Multipliers and N is the number of data. An important aspect is that some Lagrange multipliers $\left(\alpha_i, \alpha_i^* \right)$ will be zero, implying that these training objects are considered to be irrelevant for the final solution. The training objects with non-zero Lagrange multipliers are called support vectors. When linear regression is not appropriate, then input data has to be mapped into a high dimensional feature space through some nonlinear mapping (Boser et al., 1992). The two steps that are involved are first to make a fixed nonlinear mapping of the data onto the feature space and then carry out a linear regression in the high dimensional space. The input data is mapped onto the feature space by a map Φ and the dot product given by $\Phi(x_i).\Phi(x_j)$ is computed as a linear combination of the training points.

2.1 Kernel Function

The parameters involved in the nonlinear SVR model include the penalty parameter C, the error tolerance ε, and the kernel parameter. These parameters are mutually dependant, and therefore changing one value of parameter may change the other parameters. Hence, a kernel is carefully selected to match the functional properties for a nonlinear SVR. Some common kernels have been used such as polynomial (homogeneous), polynomial (non-homogeneous), radial basis function (RBF), Gaussian function, Sigmoid etc. for non-linear cases. Hsu et al. (2003) [11] suggested the RBF kernel over the linear kernel due to the nonlinearly mapping ability of the data into a featured space. A sigmoid kernel behaved like RBF kernel only for certain parameters and is not valid under some parameters (Vapnik, 1995). A polynomial kernel has more parameters than the RBF, and therefore encounters numerical obstacles. Also, the RBF kernel value ranges only from zero to one, while the polynomial kernel value ranges from zero to infinity when the degree is large. Many works on SVR in different fields indicates the centralised feature of the radial basis function for effective model of the regression process. The concept of kernel function $K\left(x_i, x_j \right) = \Phi(x_i).\Phi(x_j)$ has been introduced to reduce the computational demand (Cortes and Vapnik, 1995). So, equation (5) becomes written as

$$f_c^{'} = \sum_{i=1}^{N} \left(\alpha_i - \alpha_i^*\right) \exp\left\{ -\frac{\left(x_i - x\right)\left(x_i - x\right)^T}{2\sigma^2} \right\} \tag{6}$$

2.2 Risk Minimisation

Structural Risk Minimization (SRM) a theorem by Vapnik and Chervonekis [12], 1974 is an inductive principle for model selection used for learning from finite training data sets. Given a set of functions and examples $\{(x_1, y_1),...,(x_n, y_n)\}, x \in R, y \in r$, generated from an unknown probability distribution P{x, y}. We want to find a function $f(x_i)$ which provides the smallest possible value for the risk.

$$R[f] = \mathrm{R}_{emp}[f] + \|w\|^2 \tag{7}$$

The straightforward approach to minimize the empirical risk turns out not to guarantee a small actual risk if the number l of training examples is limited. To make the most out of a limited amount of data, novel statistical techniques have been developed during the last 25 years. The Structural Risk Minimization principle (Vapnik, 1998) is based on the fact that the above learning problem can be defined as shown in Equation (14) [8].

$$R(\alpha) \le R_{emp}[\alpha] + \sqrt{\left[\frac{h\left(\log\left(\frac{2l}{h}\right)+1\right) - \log\left(\frac{\eta}{4}\right)}{l} \right]} \tag{8}$$

The parameter h describes the capacity of a set of functions implementable by the learning machine. For binary classification h is the maximal number of point's k which can be separated into two classes in all possible 2^k ways by using functions of the learning machine. The Equation (8) depends on the chosen class of functions, whereas the empirical risk and actual risk depend on the one particular function chosen by the training procedure. The objective is to find that subset of the chosen set of functions, such that the risk bound for that subset is minimized. Clearly it is not possible to arrange data sets such that the VC dimension h varies smoothly, since it is an integer. Instead, introduce a "structure" by dividing the entire class of functions into nested subsets. For each subset, compute h or get a bound on h itself. SRM then consists of finding that subset of functions which minimizes the bound on the actual risk. This is done through simple training of a series of machines, one for each subset, where for a given subset the goal of training is simply to minimize the empirical risk. Then use the trained machine in the series whose sum of empirical risk and VC confidence is minimal.

The training and testing datasets have been chosen using sorting method to maintain statistical consistency. The application of SVM for this study requires the proper selection of design parameters (C and ε). The identification of optimal values of C and ε is largely a trial and error process. However, there are guidelines that can be used for selecting these parameters. A large C assigns higher penalties to errors so that the regression is trained to minimize error with lower generalization, while a small C assigns fewer penalties to errors; this allows the minimization of margin with errors, thus higher generalization ability. If C goes to be infinitely large, SVM would not allow the occurrence of any error and result in a complex model, whereas when C goes to zero, the result would tolerate a large amount of errors, and the model would be less complex. With regards to the selection of ε, if ε is too large, too few support vectors are selected which leads to a decrease of the final prediction performance. If ε is too small, many support vectors are selected which leads to the risk of over fitting. The optimum values of C and ε obtained in this study are presented in further. The program of SVM is constructed using MATLAB.

3 Experimental Analysis

Our experimental aim was to develop a new building material from the granite scrap, an industrial waste as a replacement material of fine aggregate in concrete. The grading of an aggregate defines the properties of different sizes in the aggregate. Sieving analysis was done in accordance with IS 383:1970 [13], IS 456:2000 [14], and the results from Figure 2. show that the crushed granite fines and sand have similar particle size properties. This clearly shows that both sand and granite fines are aggregates classified as moderately fine powder. Mix design was developed for M20 grade concrete using the IS: 10262 (2009) [15] code design and the mix ratio of cement: fine aggregate: coarse aggregate was 1: 1.86: 3.01. Through a slump test conducted as per IS 1199:1959 [16], we found the slump value decreasing with the increase in granite fines evincing difficulty in workability. The concrete for our experiments used water-cement ratio of 0.50.

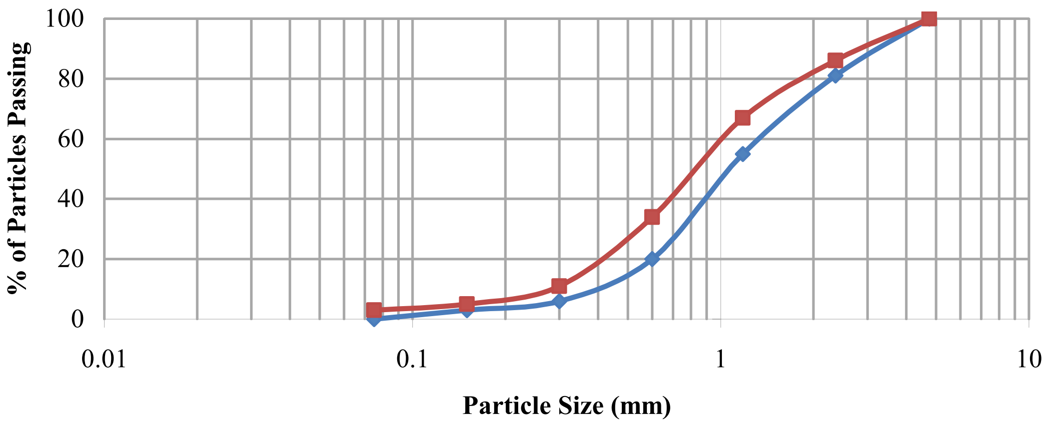

Figure 2: Particle size distribution for sand and granite fines showing the grading of aggregates

3.1 Compressive Strength

The compressive strength of concrete increased when granite powder were used. Complete replacement of river sand with granite fines yielded a low compressive strength value indicating river sand cannot be fully replaced by granite fines. The partial replacement of sand with granite fines yielded 7 and 28 days peak compressive strength value of 34.4N/mm^2 and 46.8N/mm^2 respectively at 35% replacement level. The complete results obtained for both 7 and 28 days through standard compressive strength analysis are shown in Table 1, 2.

Increase in compressive strength associated with partial replacement of sand with granite fines can be attributed to frictional resistance's component's contribution to compressive strength arising from the rough and irregular nature of granite fines particles that fills the voids between the gravel and sand particles while cement binds the components together. Strength obtained with the use of only river sand as fine aggregate and river gravel as coarse aggregate is dependent more on the bonding strength of cement that fills the voids between the coarse aggregate and the river sand particles as its frictional resistance contribution to strength is less due to smooth and rounded nature of river gravel and sand particles used as coarse and fine aggregate respectively. It is also proved that the compressive strength increases with the increase in days of curing for all the mixtures. The reduction in strength may be due to the effect of higher evaporation rates from the concrete specimens during curing.

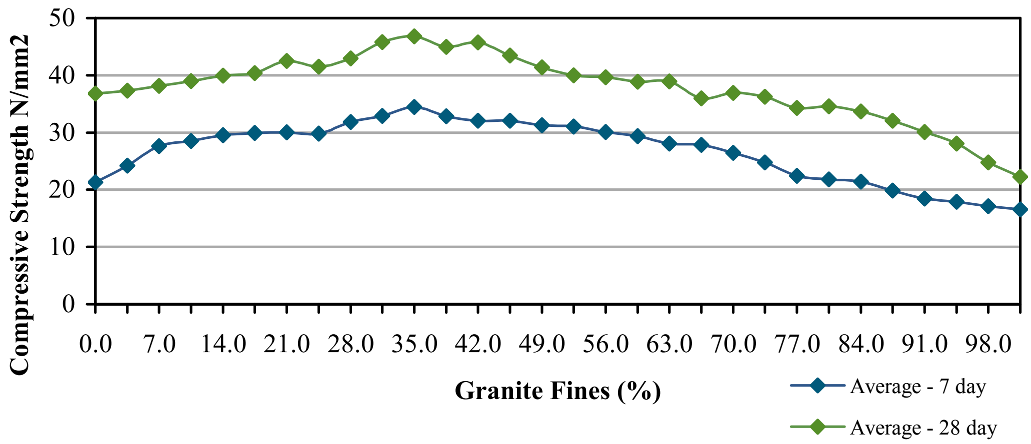

Figure 3: Comparison of 7, 28-day compressive strength with the addition of granite fines

Figure 3. clearly shows the results from the replacement of sand using granite fines. But one must understand the implications caused due to the fluctuations created in the graphs due to human and experimental errors. These errors may be due to the temperature variances, time duration of curing, humidity conditions, and other human errors. Therefore, it will be strenuous to adopt the graph as the final outcome for the optimum percentage of granite fines. These changes are addressed in the prediction of the outcome using support vector machines. SVM analyses the

boundary and identifies the support vectors creating a set of equations to predict the outcome of compressive strength values.

3.2 Data Set

The datasets given below are the compressive strengths results of granite fines mixed concrete. The datasets collected are the compressive strength values obtained by changing the percentage of granite fines from 0 - 100 at intervals of 3.5% for mixing, then curing and finally testing for their compressive strengths. The collected data sets have been further divided in two sub data sets, a training dataset, to construct the model, and a testing dataset to estimate the model performance. The training and testing datasets are normalised, i.e. between 0 and 1. This was done to verify the accuracy of the model based function. Each of the data set had been normalised to reduce the initial error and size of data. The following Tables 1, 2. show the normalised values of our 30 results as 70% training data set and 30% testing data set respectively. In training process, a simple trial-and-error approach has been used to select the design value of C, ε and width σ of radial basis function.

Granite Fines	**Normalized Value**	**Compressive Strength Average - 7 day**	**Normalized Value**	**Compressive Strength Average - 28 day**	**Normalized Value**
%		**N/mm²**		**N/mm²**	
0.0	0.00	21.3	0.27	36.8	0.59
7.0	0.07	27.6	0.62	38.1	0.65
10.5	0.11	28.5	0.67	39.0	0.68
14.0	0.14	29.5	0.73	39.9	0.72
24.5	0.25	29.8	0.74	41.5	0.78
28.0	0.28	31.8	0.85	43.0	0.84
31.5	0.32	32.9	0.91	45.8	0.96
35.0	0.35	34.4	1.00	46.8	1.00
42.0	0.42	32.0	0.87	45.7	0.96
45.5	0.46	32.0	0.87	43.5	0.86
52.5	0.53	31.1	0.81	40.0	0.72
56.0	0.56	30.1	0.76	39.6	0.71
63.0	0.63	28.1	0.64	38.9	0.68
66.5	0.67	27.9	0.63	36.0	0.56
70.0	0.70	26.4	0.55	36.9	0.60
73.5	0.74	24.8	0.46	36.3	0.57
77.0	0.77	22.4	0.33	34.3	0.49
84.0	0.84	21.4	0.27	33.7	0.47
87.5	0.88	19.9	0.18	32.0	0.40
91.0	0.91	18.4	0.10	30.1	0.32
98.0	0.98	17.1	0.03	24.8	0.10

Table 1: Normalised data for Training Output

Granite Fines	Normalized Value	Compressive Strength Average - 7 day	Normalized Value	Compressive Strength Average - 28 day	Normalized Value
%		N/mm^2		N/mm^2	
3.5	0.04	24.2	0.43	37.3	0.61
17.5	0.18	29.9	0.75	40.4	0.74
21.0	0.21	30.0	0.75	42.5	0.82
38.5	0.39	32.8	0.91	45.0	0.93
49.0	0.49	31.3	0.82	41.4	0.78
59.5	0.60	29.4	0.72	38.9	0.68
80.5	0.81	21.8	0.29	28.1	0.50
94.5	0.95	17.9	0.07	24.8	0.24

Table 2: Normalised data for Testing Output

4 Results and Discussion

In this study, the performance of the SVM tool was also known from coefficient of correlation, R. For the training dataset from the 7-day compressive strength, the design values of C, ε and σ were 500, 0.01 and 1 respectively. Concurrently, the testing dataset from 7-day compressive strength showed design value of C, ε and σ as 500, 0.01 and 1 respectively. The equation obtained based on the developed SVM model to predict the compressive strength as follows, $f_c' = \sum_{i=1}^{N}\left(\alpha_i - \alpha_i^*\right)\exp\left\{-\frac{\left(x_i - x\right)\left(x_i - x\right)^T}{2\sigma^2}\right\}$ where N=21, σ=1 and b=0. The following Figures 4, 6. give the performance of training and testing dataset for the 7-day compressive strength using support vector machines.

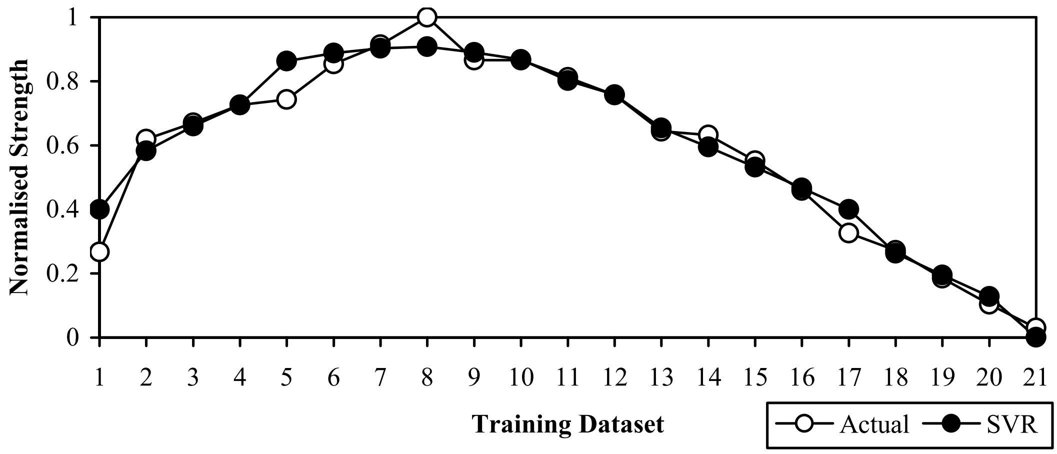

Figure 4: Performance of training dataset for 7-day Compressive Strength using SVM

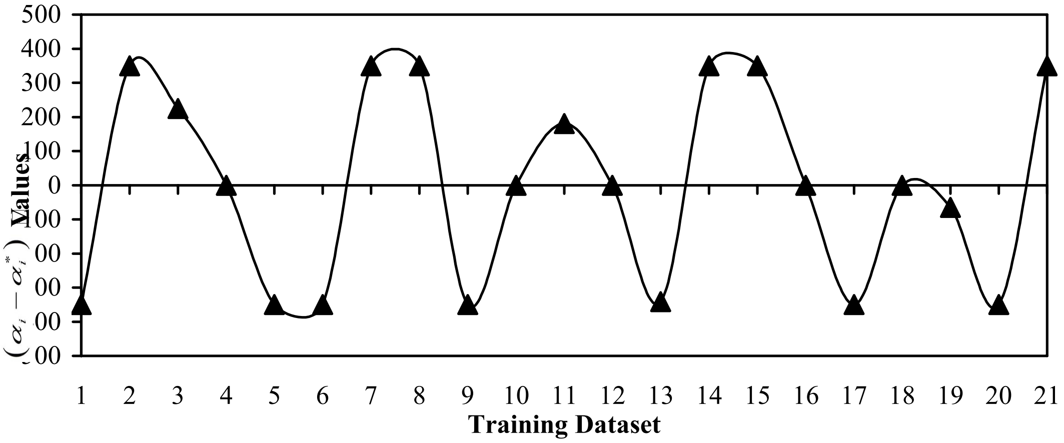

Figure 5: Values of $\left(\alpha_i - \alpha_i^*\right)$ for compressive strength for 7-day training dataset using SVM

The derived values of $\left(\alpha_i - \alpha_i^*\right)$ 7-day compressive strength from the training dataset are given in Figure 3. From the $\left(\alpha_i - \alpha_i^*\right)$ values, we can compute the compressive strength for the testing dataset from the following equation $f_c^{'} = \sum_{i=1}^{21}\left(\alpha_i - \alpha_i^*\right)\exp\left\{-\frac{\left(x_i - x\right)\left(x_i - x\right)^T}{2(1)^2}\right\}$.

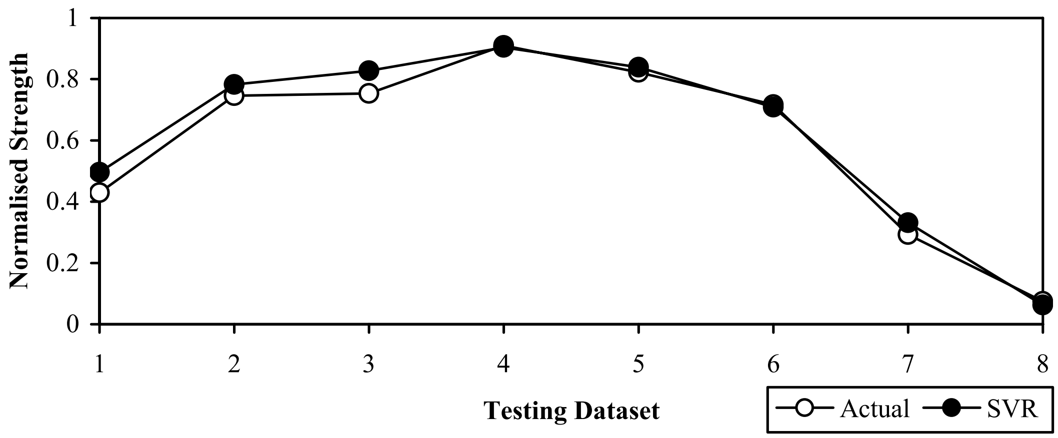

Figure 6: Performance of testing dataset for 7-day Compressive Strength using SVM

The R value of combined training and testing dataset were calculated to be 0.986. The R value, being close to 1, shows that the function obtained proves a good model. For the training and testing dataset of 28-day compressive strength, the design values of C, ε and σ are 350, 0.01 and 1 respectively. The equation obtained based on the developed SVM model to predict the compressive strength as follows $f_c^{'} = \sum_{i=1}^{N} \left(\alpha_i - \alpha_i^*\right) \exp\left\{ -\frac{\left(x_i - x\right)\left(x_i - x\right)^T}{2\sigma^2} \right\}$, where N=21, σ=1 and b=0. The following Figures 7, 9. give the performance of training and testing dataset for the 28-day compressive strength using support vector machines. The derived values of $\left(\alpha_i - \alpha_i^*\right)$ 28-day compressive strength from the training dataset are given in Figure 6. From the $\left(\alpha_i - \alpha_i^*\right)$ values, we can compute the compressive strength $f(x) = \sum_{i=1}^{N} \left(\alpha_i - \alpha_i^*\right) K\left(x_i, x_j\right) + b$ for the testing dataset.

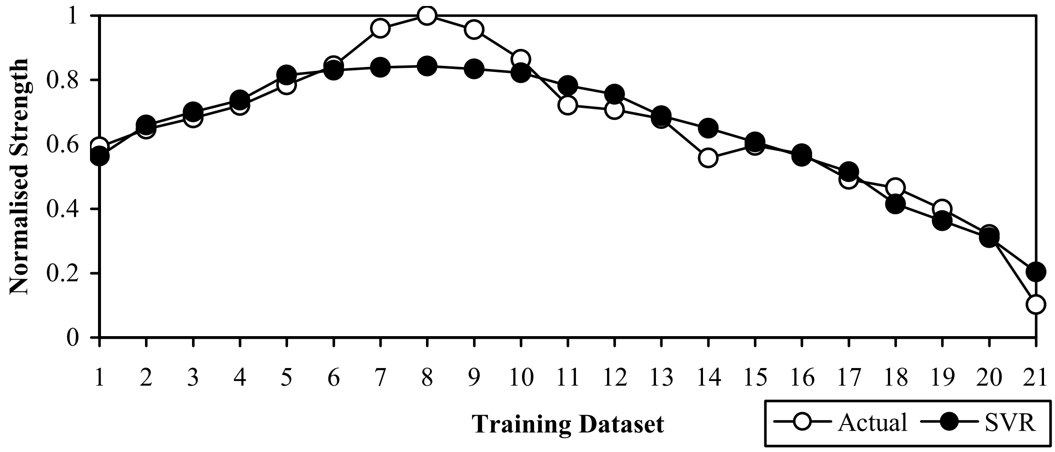

Figure 7: Performance of training dataset for 28-day Compressive Strength using SVM

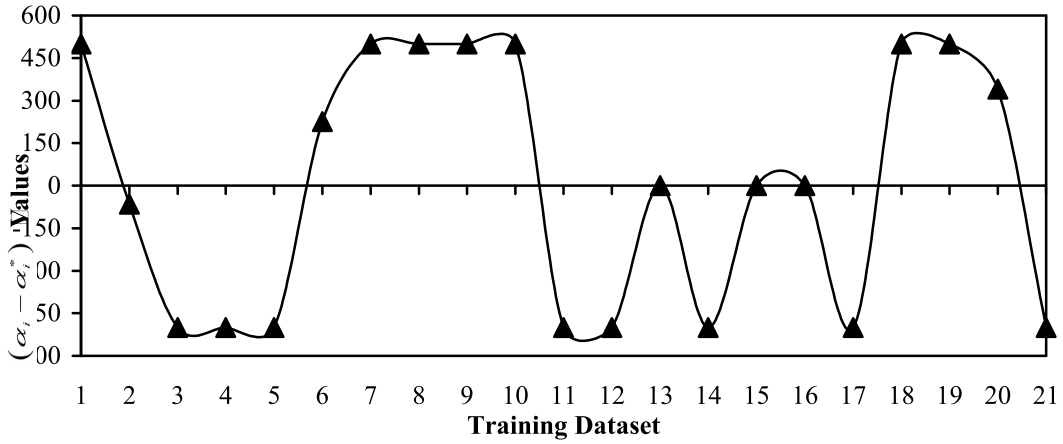

Figure 8: Values of $\left(\alpha_i - \alpha_i^*\right)$ for compressive strength for 28-day training dataset using SVM

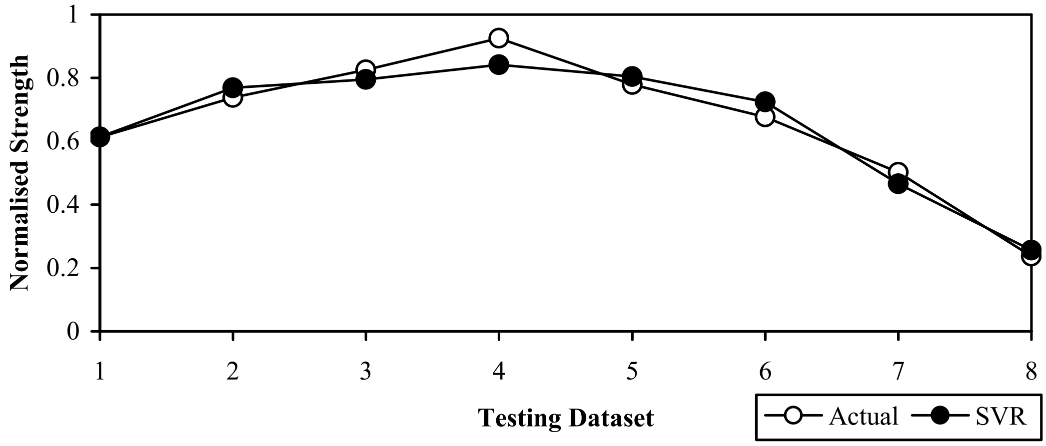

Figure 9: Performance of testing dataset for 28-day Compressive Strength using SVM

The R value of combined training and testing dataset was calculated to be 0.965. The Figure 10. below illustrates the correlation between the actual output and the predicted output. The output predicted shares a correlation coefficient close to 1, thus proving in both the cases, i.e. 7-day and 28-day compressive strengths, that the developed SVM has the ability to predict compressive strength f_c'.

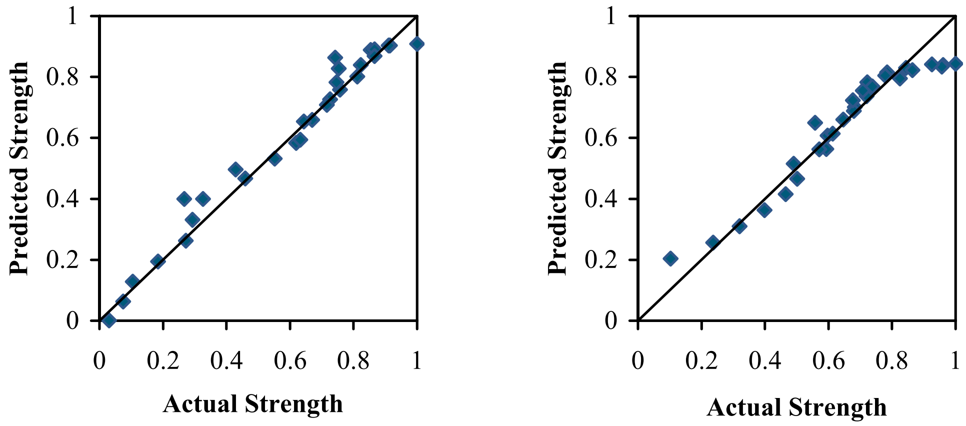

Figure 10: Comparison between 7-day and 28-day dataset for actual and predicted compressive strength using SVM

The beta values $\left(\alpha_i - \alpha_i^*\right)$ show the developed SVM used 21 training data sets for support vector prediction of compressive strength. These beta values have only been used for final prediction. So, there is real advantage gained in terms of sparsity. Sparseness is desirable in SVM for several reasons, namely (Figueiredo, 2003):

- Sparseness leads to a structural simplification of the estimated function.
- Obtaining a sparse estimate corresponds to performing feature/variable selection.

- The generalisation ability improves with the degree of sparseness.

Sparseness means that a significant number of the weights are zero (or effectively zero), which has the consequence of producing compact, computationally efficient models, which in addition are simple and therefore produce smooth functions. Thus, the developed SVM model successfully captured input and output relationship for training and testing dataset. Therefore, we can come to a conclusion stating the developed SVM model being able to predict the compressive strength value accurately.

5 Conclusion

The compressive strength of M20 concrete increased when granite powder were used. Based on the compressive strength analysis, the replacement of sand with 35% of granite fines is recommended for use in the construction of highly trafficked rigid pavements. The partial replacement of granite fines with sand gave a 7-days and 28-days peak compressive strength value of 34.4N/mm^2 and 46.8N/mm^2 at 35% replacement level. In conclusion, the addition of granite powder has shown a prominent increase in the compressive strength of concrete for the M20 mix. This study has also successfully applied support vector machines for the prediction of the compressive strength of concrete. The performance of the developed support vector machine is better than the available methods. Support vector machine training consists of solving a – uniquely solvable – quadratic optimisation problem and always finds a global minimum. The user can use the equations developed for the determination of the compressive strength of concrete with partial replacement of sand by granite. The proposed support vector machine is not a substitute but may be a viable alternative for prediction of the compressive strength of concrete.

References

[1] R. Ilangovan., K. Nagamani, "Application of Quarry Dust in Concrete construction. High performance Concrete", Federal highway Administration, 1-3, 2007.

[2] T.S. Nagaraj, Banu, Zahida, "Efficient utilization of rock dust and pebbles as aggregates in Portland cement concrete", Indian Concrete Journal, 70(I):1:4, 1996.

[3] S.N. Raman, M.D. Safiuddin, M.F.M. Zain, "Utilization of Quarry Waste Fine Aggregate in Concrete Mixtures", Journal of Applied Sciences Research, Insinet Publication, 3(3), 202-208, 2007.

[4] L.J. Murdock, K.M. Brook, J.D. Dewar, "Concrete Materials and Practice", Edward Arnold London, 1991.

[5] B. Scholkopf, "Support Vector Learning", R. Oldenbourg Verlag, Munchen. Doktorarbeit, TU Berlin, 1997.

[6] B.E. Boser, I.M. Guyon, and V.N. Vapnik, "A training algorithm for optimal margin classifiers", Proceedings of the Annual Conference on Computational Learning Theory. ACM Press, Pittsburgh, PA, 144–152, 1992.
[7] C. Cortes, V.N. Vapnik, "Support vector networks Machine Learning", 20: 273–297, 1995.
[8] V.N. Vapnik, "Statistical Learning Theory", New York: John Wiley and Sons, 1998.
[9] V.N. Vapnik, "The Nature of Statistical Learning Theory", New York: Springer-Verlag, 1995.
[10] A.J. Smola, "Regression estimation with support vector learning machines", Master's Thesis, Technische Universität München, Germany, 1996.
[11] Chun-Nan Hsu, Chia-Hui Chang, Harianto Siek, Jiann -Jyh Lu and Jen- Jie Chiou, "Reconfigurable Web Wrapper Agents for Web Information Integration", In Proceedings of IJCAI-2003 Workshop on Web Information Integration, 2003.
[12] V.N. Vapnik, A. Chervonenkis, "Theory of Pattern Recognition", Moscow, Nauka, 1974.
[13] IS 383:1970 (R2002) Specifications For Coarse And Fine Aggregates.
[14] IS 456:2000 Plain and Reinforced Concrete.
[15] IS 10262:2009, Concrete Mix Proportioning Guidelines Bureau Ind. Stds.
[16] IS 1199:1959. Method of sampling and analysis of concrete.