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Modeling properties of self-compacting concrete: support vector machines approach

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Abstract. The paper explores the potential of Support Vector Machines (SVM) approach in predicting 28-day compressive strength and slump flow of self-compacting concrete. Total of 80 data collected from the exiting literature were used in present work. To compare the performance of the technique, prediction was also done using a back propagation neural network model. For this data-set, RBF kernel worked well in comparison to polynomial kernel based support vector machines and provide a root mean square error of 4.688 (MPa) (correlation coefficient=0.942) for 28-day compressive strength prediction and a root mean square error of 7.825 cm (correlation coefficient=0.931) for slump flow. Results obtained for RMSE and correlation coefficient suggested a comparable performance by Support Vector Machine approach to neural network approach for both 28-day compressive strength and slump flow prediction.

Keywords: 28-day compressive strength; slump flow; prediction; Support vector machines technique; neural network.

1. Introduction

Different types of concrete like high performance concrete, self-compacting concrete, ready mixed concrete etc., consist of some well-defined constituents such as cement, water, fine aggregate, coarse aggregate etc. Concrete is the most important and significant structural material being used in the construction industry. The strength of concrete is considered as one of the most important property for a given concrete mix design. Traditionally, a concrete mix is designed based on the code recommendations as well by using previous experiences. The tests for compressive strength are carried out at about 7 or 28 days from the date of placing the concrete. If due to some experimental error in designing the mix, the test results fall short of required strength, the entire process of concrete design has to be repeated which may be a costly and time consuming process. Thus, the need of some suitable methodology was felt to estimate the compressive strength of concrete based on its constituents at the time of design, before placing it.

Prediction of compressive strength of concrete is important for concrete construction as it gives an idea about the time for formwork removal, project scheduling and quality control. Several

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approaches using regression functions were proposed for predicting the concrete strength (Snell, *et al*. 1989, Chengju 1989, Oluokun, *et al.* 1990, Popovics 1998). Lee, *et al*. (2007) estimated the strength of ready-mixed concrete using support vector regression (SVR) approach. Traditional modelling approaches are based on empirical relationships derived from the experimental data. Within last decade, researchers have explored the potential of artificial neural networks (ANNs), a nonlinear modeling approach, in predicting the compressive strength of the concrete due to its ability to learn input-output relation for any complex problem in an efficient way. Several work reported the use of neural network based modeling approach in predicting the concrete strength (Lai and Serra 1997, Yeh 1998a, 1998b, 1999, Kasperkiewicz, *et al.* 1995, Sebastia, e*t al*. 2003, Kim, *et al.* 2004, Dias and Pooliyadda, 2001, Oh, *et al*. 1999, Hong-Guang and Ji-Zong, 2000, Ren and Zhao 2002, Lee 2003). Ji and Lin (2006) proposed prediction models of strength and workability of mortar based on artificial neural networks. The use of Neural Network in predicting the workability which has direct effect on the strength of concrete has been reported by Yeh (2008).

In most of the studies, a back propagation neural network was used. A neural network model requires no functional relationship among the variables, as is the case with most of other regression analysis techniques. A neural network based modelling algorithm requires setting up of different learning parameters (like learning rate, momentum), the optimum number of nodes in the hidden layer and the number of hidden layers so as to have a less complex network with a relatively better generalization capability. A large number of training iterations may force ANN to over train, which may affect the predicting capabilities of the model.

Within last few years, another modeling technique called Support Vector Machines (SVMs), proposed by Vapnik (1995) is being applied in the field of civil engineering (Dibike, *et al.* 2001, Pal and Mather 2003).

Self-Compacting concrete is defined as the type of high performance concrete, which fills all corners of formwork without vibration. It has good deformability, high segregation resistance and no blocking around reinforcement. SCC was developed initially in Japan in the 1980's (Okamura 1997) and later adopted in countries like USA, UK, Europe, and Asian countries as well. The successful development of SCC must ensure a good balance between deformability and stability. It requires the manipulation of several mixture variables to ensure acceptable rheological behaviour and proper mechanical properties. Some guidelines which have been set for mixture proportioning of SCC are i) reducing the volume ratio of aggregate to cementitious material; increasing the paste volume and water-cement ratio (w/c); ii) controlling the maximum coarse aggregate particle size and total volume; and iii) using various viscosity-enhancing admixtures (VEA) (Nagamoto and Ozawa, 1997). Also, absence of theoretical relationships between mixture proportioning and measured engineering properties of SCC makes it more complex. Some attempts have been made to describe these properties using traditional regression analysis tools and statistical models (Sonebi 2004a, Sonebi 2004b).

One major issue in the design of an artificial neural network is the determination of suitable architecture. A back propagation neural network based modelling algorithm requires setting up of different learning parameters (like learning rate, momentum etc), the optimal number of nodes in the hidden layer and the number of hidden layers so as to have a less complex network with a relatively better generalization capability. In most of the reported applications, selection of a number of hidden layers and the number of nodes in hidden layer is done by using a rule of thumb or trying several arbitrary architectures and selecting one that gives the best performance. Further, a suitable value of parameters like learning rate and momentum is also required for selected hidden layers and nodes. Design of a neural network involves in using non-linear optimisation problem that provides a local minima. During training process a large number of training iterations may force artificial neural networks to over train, which may affect the predicting capabilities of the model. Several studies suggested using a validation data set (i.e. a data set other than the training data set) to have an idea about the suitable number of iterations for a specific data set. This may be a problem for studies where number of data set is limited, like concrete strength predictions. Choice of a suitable architecture has always been a problem with neural network approach and requires a lot of efforts and computational cost. Presence of local minima due to the use of a non-linear optimization problem with a back propagation neural network approach is another drawback while the advantage of using Support Vector Machines is its speed and requiring no user-defined parameter.

The objective of the present study was to examine the potential of support vector machines (SVMs) for predicting the slump flow and 28-day compressive strength of SCC mixtures and was found to work well in comparison to much used neural network approach (Nehdi, *et al*. 2001). The complex relationship between mixture proportions and engineering properties of SCC is generated based on existing data in the open Literature.

2. Support vector machines

Support vector machines (SVMs) are classification and regression methods, which have been derived from statistical learning theory (Vapnik 1995). The SVMs classification methods are based on the principle of *optimal separation* of classes. If the classes are separable – this method selects, from among the infinite number of linear classifiers, the one that minimize the generalization error, or at least an upper bound on this error, derived from structural risk minimization. Thus, the selected hyper plane will be one that leaves the maximum margin between the two classes, where margin is defined as the sum of the distances of the hyper plane from the closest point of the two classes (Vapnik 1995).

If the two classes are non-separable, the SVMs try to find the hyper plane that maximizes the margin and at the same time, minimizes a quantity proportional to the number of misclassification errors. The trade off between margin and misclassification error is controlled by a positive constant that has to be chosen beforehand. This technique of designing SVMs can be extended to allow for non-linear decision surfaces. This can be achieved by projecting the original set of variables into a higher dimensional feature space and formulating a linear classification problem in the feature space (Vapnik 1995). The formulation of support vector machines so that it can be applied to regression problems can be as given by Vapnik (1995) for ε-Support Vector Regression (SVR). The purpose of the SVR is to find a function having at most ε deviation from the actual target vectors for all given training data and have to be as flat as possible (Smola 1996).

3. Details of SVMs

As discussed in previous section, in situations with non-linear decision surfaces, support vector machines use a mapping to project the data in a higher dimensional feature space. To make computation simpler, the concept of the kernel is introduced. A number of kernels are discussed in the literature, but it is difficult to choose one, which gives the best generalisation with a given data set. As the choice of kernel may influence the prediction capabilities of the SVMs, present study uses a polynomial

$$K(x,y) = ((x \cdot y) + 1)^d \tag{1}$$

and a radial basis kernel

$$K(x,y) = e^{-\gamma| x-y |^2}) \tag{2}$$

where d and γ are kernel specific parameters.

The use of SVMs requires setting of user-defined parameters such as regularisation parameter (C), type of kernel, kernel specific parameters and error-insensitive zone ε. Variation in error-insensitive zone ε found to have no effect on the predicted compressive strength and a value of 0.0010 was chosen for all experiments. The optimum value of parameters C, d and γ were obtained after a large number of trials by varying these values for different data sets used in present study. The correlation coefficients and Root Mean Square Error (RMSE) values were compared to reach at a suitable choice of these parameters. Cross-validation is used to generate the model with SVMs on the input data set and predicting the 28-day compressive strength and slump flow of the data sets used in the study. The cross-validation is a method of estimating the accuracy of a classification or regression model. All computations were carried out using a PIV personnel computer with 256 MB of RAM. It requires a small computational time to reach at a suitable choice of user-defined parameter with both data sets. SVM software used in present study is based on sequential minimisation optimisation (Platt 1999) as implemented by Witten and Frank (2000).

4. Database

The model's success in predicting the behaviour of SCC mixtures depends on comprehensiveness of the training data. Availability of large variety of experimental data is required to develop the relationship between the mixture variables of SCC and its measured properties. The basic parameters considered in this study were cement content, sand content, coarse aggregate content, pulverised fly ash (PFA), water-to-powder ratio and superplasticizer dosage (Percentage of quantity of superplasticizer with reference to total powder content i.e. Cement + PFA) added. The response was derived for slump flow and 28-day compressive strength. The data were identified from the literature having mixture component with comparable physical and chemical properties. The exclusion of one or more of SCC properties in some studies and the ambiguity of mixture

Table 1a Source of training data

S. No.	Source of training data	No. of training data	Data used for prediction
1.	Bouzoubaa and Lachemi (2001)	9	Slump flow, 28-day compressive strength
2.	Ghezal and Khayat (2002)	18	Slump flow, 28-day compressive strength
3.	Bui, *et al.* (2002)	14	28-day compressive strength
4.	Patel, *et a*l. (2004)	21	Slump flow, 28-day compressive strength
5.	Sonebi (2004)	18	Slump flow, 28-day compressive strength

Table 1b Values of different parameters

Sr. No.	Cement (kg/m^3)	PFA (kg/m^3)	W/B	SP (%)	Sand (kg/m^3)	Coarse Aggregate (kg/m^3)	Slump flow (cm)	28-day Compressive Strength (MPa)	Source of Training Data
1	290	100	0.45	0.80	913	837	43.40	42.70	Sonebi (2004)
2	250	261	0.55	0.50	478	837	70.50	17.00	
3	210	100	0.65	0.80	910	837	57.50	19.10	
4	250	160	0.55	0.50	742	837	62.50	24.10	
5	210	220	0.45	0.80	768	837	55.50	26.70	
6	290	100	0.65	0.20	709	837	62.30	26.60	
7	290	220	0.45	0.20	625	837	34.50	32.90	
8	250	160	0.55	0.50	742	837	60.50	26.00	
9	250	160	0.55	0.50	742	837	62.50	28.50	
10	250	160	0.55	0.50	742	837	60.50	26.40	
11	250	160	0.55	0.00	739	837	41.90	27.30	
12	317	160	0.55	0.50	594	837	69.70	29.10	
13	210	220	0.65	0.20	562	837	73.70	10.20	
14	250	160	0.55	0.50	742	837	60.00	25.30	
15	250	160	0.38	0.50	919	837	20.00	36.30	
16	250	160	0.55	1.00	746	837	79.00	26.70	
17	250	160	0.72	0.50	566	837	88.00	11.00	
18	183	160	0.55	0.50	891	837	36.10	22.10	
19	220	180	0.39	0.35	916	900	59.00	49.00	
20	220	180	0.39	0.35	916	900	59.00	49.00	
21	160	240	0.39	0.35	886	900	63.00	44.00	
22	193	158	0.39	0.35	1024	900	41.00	44.00	
23	220	180	0.45	0.35	850	900	76.00	38.00	
24	198	232	0.34	0.20	874	900	54.00	46.00	
25	248	203	0.39	0.35	808	900	68.00	50.00	Patel, *et al.* (2004)
26	237	133	0.36	0.20	1034	900	33.00	49.00	
27	220	180	0.39	0.35	916	900	57.00	49.00	
28	237	133	0.43	0.50	960	900	65.00	46.00	
29	275	155	0.43	0.50	827	900	81.00	48.00	
30	280	120	0.39	0.35	946	900	51.00	45.00	
31	170	200	0.43	0.20	930	900	60.00	31.00	
32	220	180	0.39	0.60	916	900	77.00	43.00	
33	220	180	0.39	0.35	916	900	60.00	47.00	
34	220	180	0.39	0.10	916	900	38.00	44.00	
35	198	232	0.36	0.50	872	900	71.00	52.00	
36	220	180	0.39	0.35	916	900	58.00	45.00	
37	220	180	0.33	0.35	982	900	35.00	51.00	
38	170	200	0.43	0.50	928	900	76.00	33.00	
39	275	155	0.43	0.20	830	900	48.00	36.00	
40	247	165	0.45	0.12	845	846	24.00	34.60	
41	238	159	0.40	0.29	844	844	24.00	37.80	
42	232	155	0.35	0.38	846	847	24.00	48.30	

NA - Not used for modelling slump flow

Table 1b Continued.

Sr. No.	Cement (kg/m^3)	PFA (kg/m^3)	W/B	SP (%)	Sand (kg/m^3)	Coarse Aggregate (kg/m^3)	Slump flow (cm)	28-day Compressive Strength (MPa)	Source of Training Data
43	207	207	0.45	0.40	845	843	23.00	33.20	Bouzoubaa & Lachemi (2001)
44	200	200	0.40	0.17	842	843	24.00	34.90	
45	197	197	0.35	0.28	856	856	24.00	38.90	
46	169	254	0.45	0.00	853	853	23.00	30.20	
47	163	245	0.40	0.20	851	851	24.00	26.20	
48	161	241	0.35	0.30	866	864	24.00	35.80	
49	350	162	0.59	0.09	768	840	NA	51.70	
50	349	162	0.57	0.15	779	852	NA	59.90	
51	350	133	0.53	0.17	815	883	NA	55.30	
52	350	111	0.51	0.16	831	900	NA	61.00	Bui, *et al.*(2002)
53	250	257	0.77	0.12	787	853	NA	51.50	
54	427	115	0.46	0.13	779	844	NA	59.40	
55	348	224	0.50	0.44	783	848	NA	58.60	
56	350	90	0.49	0.15	852	923	NA	46.50	
57	327	173	0.54	0.20	902	803	NA	61.60	
58	380	145	0.48	0.10	788	854	NA	73.50	
59	350	186	0.51	0.11	786	851	NA	70.40	
60	380	145	0.48	0.14	988	659	NA	65.50	
61	380	192	0.53	0.11	931	621	NA	67.80	
62	275	250	0.67	0.10	775	840	NA	54.50	
63	325	60	0.65	0.43	899	850	67.00	30.80	
64	325	60	0.65	0.43	899	850	66.50	32.60	
65	325	120	0.75	0.43	755	850	75.50	32.20	
66	249	60	0.68	0.43	1079	850	20.20	24.00	
67	325	60	0.85	0.43	722	850	88.50	13.30	
68	370	96	0.57	0.25	833	850	24.00	39.50	
69	400	60	0.63	0.43	718	850	78.50	30.40	Ghezal & Khayat (2002)
70	325	60	0.65	0.43	899	850	62.50	35.30	
71	370	24	0.69	0.62	770	850	86.00	18.70	
72	325	0	0.55	0.43	1042	850	23.00	41.20	
73	280	96	0.87	0.25	820	850	66.00	19.60	
74	325	60	0.65	0.75	896	850	68.00	27.70	
75	325	60	0.65	0.43	898	850	68.50	35.00	
76	325	60	0.65	0.12	900	850	23.00	31.40	
77	370	96	0.57	0.62	830	850	68.50	38.80	
78	325	60	0.65	0.43	898	850	66.00	34.30	
79	280	96	0.87	0.62	817	850	79.50	15.90	
80	370	24	0.69	0.25	772	850	70.50	26.40	

NA - Not used for modelling slump flow

proportions and testing methods in others was responsible for setting the criteria for identification of data. Table 1a, b gives the description of the data identified from the literature.

The training of Support Vector Machines was carried out using pair of input vector and output vector. The Support Vector Machines was designed using 69 pairs of input and output vectors for slump flow and 80 data for 28-day compressive strength prediction. The data sets were collected from studies by Bouzoubaa and Lachemi (2001), Ghezal and Khayat (2002), Bui, *et al.* (2002), Patel, *et al*. (2004) and Sonebi (2004a, b) as given in table 1a and values of different parameters as given in table 1b . Input vector consisted of mixture variables and an output vector of one element i.e. slump flow and 28-day compressive strength. For slump flow and 28-day compressive strength prediction, the input parameters were weight of cement (kg/m^3), sand (kg/m^3), coarse aggregate (kg/m^3), water-binder ratio, superplasticizer (%) and PFA (kg/m^3). A back propagation neural network was also used to compare its performance with Support Vector Machines based approaches.

5. Results and analysis

The acceptance/rejection of the model developed was determined by its ability to predict the slump flow and 28-day compressive strength of SCC. Also, a successfully trained model is characterized by its ability to predict slump flow and 28-day compressive strength values for the data it was trained on. Several trials were carried out to find the suitable choice of parameter C and kernel specific parameters in predicting the strength of high strength concrete data. Table 2 gives the values of user-defined parameters for both polynomial and RBF kernels in predicting the 28-day concrete strength and slump flow. A 10-fold cross validation was used to predict the slump flow and 28-day compressive strength for the data set used in this study. The cross validation is the method of accuracy of a classification or regression model. The input data set is divided into several parts (a number defined by the user), with each part intern used to test a model fitted to the remaining part. The correlation coefficient and root mean square error (RMSE) was used to judge

Table 2 Values for various parameters of Support Vector Machines

	RBF kernel		Polynomial kernel	
Parameter	C	γ	C	D
28-day compressive strength (MPa)	20	0.25	20	2.0
Slump flow(cm)	2	4	2	2.0

Table 3 Summary of coefficients by Neural Network (NN) and Support Vector Machines

Methodology	Property	Correlation Coefficient	Mean Absolute Error	Root Mean Square Error
NN	Slump flow (cm)	0.914	7.085	8.778
	28-day compressive Strength(MPa)	0.906	4.819	6.005
SVM(rbf)	Slump flow (cm)	0.931	5.606	7.825
	28-day compressive Strength(MPa)	0.942	3.695	4.688
SVM(poly)	Slump flow (cm)	0.916	6.286	8.817
	28-day compressive strength (MPa)	0.935	3.888	5.057

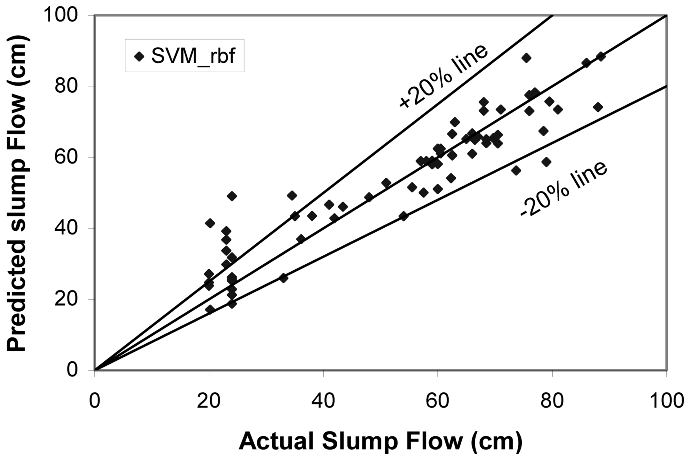

Fig. 1 Graph for actual v/s predicted slump flow (cm) by using Radial basis kernel of support vector machines

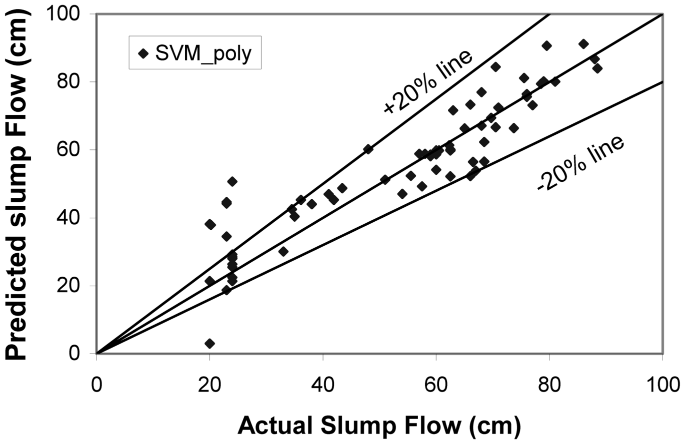

Fig. 2 Graph for actual v/s predicted slump flow (cm) by using polynomial based kernel of support vector machines

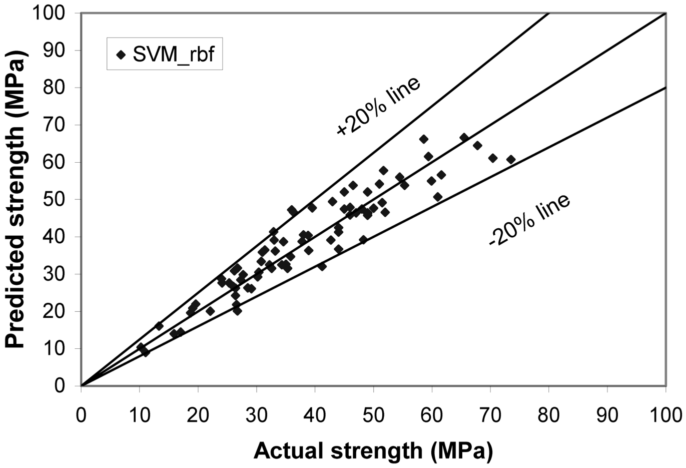

Fig. 3 Graph for actual v/s predicted strength (MPa) by using radial basis kernel of support vector machines

the performance of Support Vector Machines as well of the neural network approach in predicting the slump flow and strength.

Table 3 provides the correlation coefficient and RMSE obtained with this data using Support Vector Machines to predict the slump flow and 28-day compressive strength. To compare the performance of Support Vector Machines, graphs between actual and predicted slump flow and 28-day compressive strength were plotted. The performance of Support Vector Machines approach in predicting the slump flow is shown in Fig. 1 and Fig. 2 for SVM (RBF) and SVM (Polynomial) respectively and for predicting 28-day compressive strength for this data set is shown in Fig. 3 and Fig. 4 for SVM (RBF) and SVM (Polynomial) respectively. Results suggest that most of the points are lying within ±20% of the line of perfect agreement, which suggest that Support Vector Machines approach can effectively be used to predict the compressive strength for self-compacting

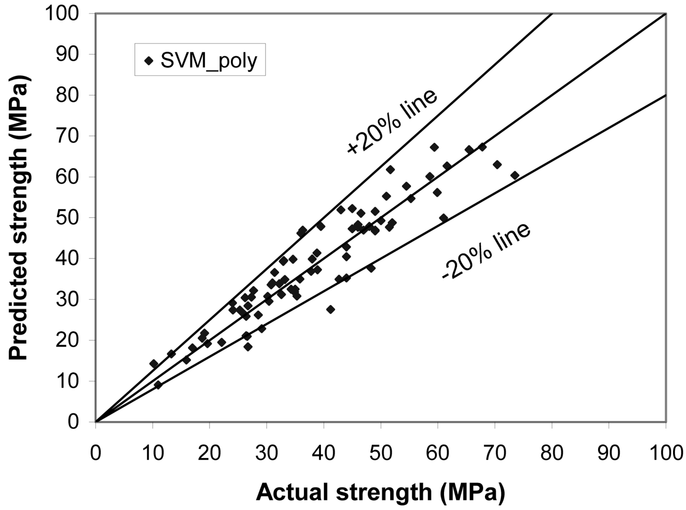

Fig. 4 Graph for actual v/s predicted strength (MPa) by using polynomial based kernel of support vector machines

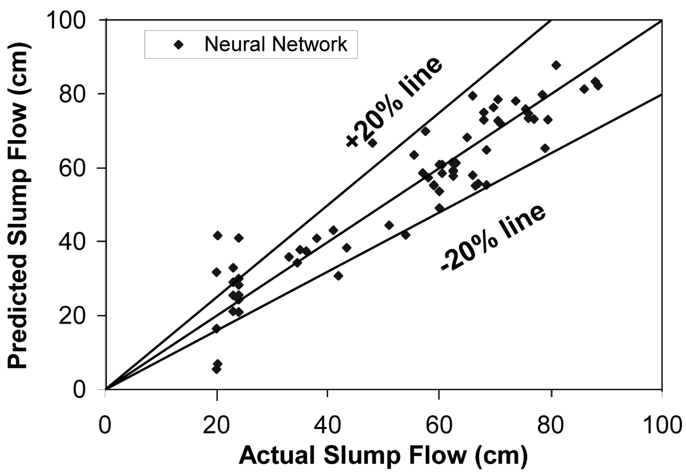

Fig. 5 Actual v/s Predicted value for Slump Flow (cm) by Neural Network

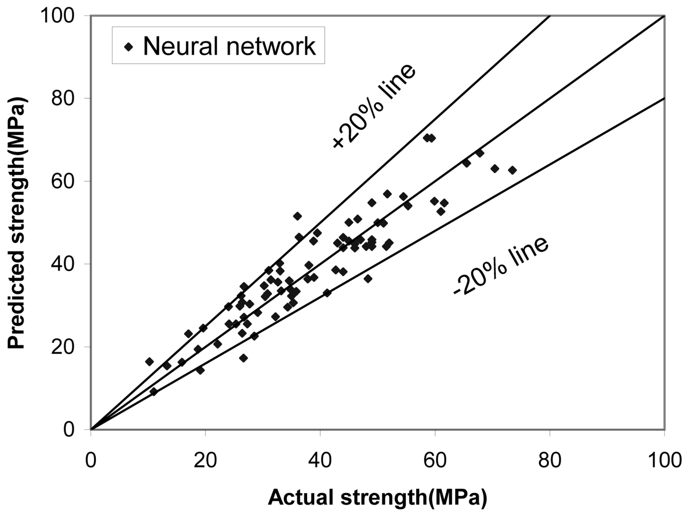

Fig 6 Actual v/s Predicted value for Strength (MPa) by Neural Network

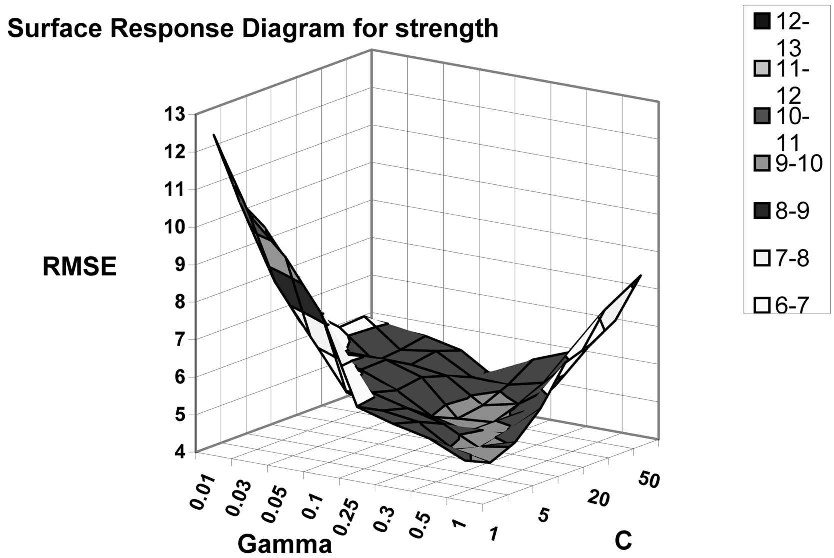

Fig. 7 Response Surface Diagram for Interaction between C and Gamma for Strength

concrete data. A correlation coefficient of 0.942 and 0.935 (RMSE=4.688 and 5.057) were achieved with support vector machines radial based and polynomial based approaches respectively. Results suggested a better performance by Support Vector Machines for this data set in slump flow prediction also. Most of the points are again lying within ±20% of the line of perfect agreement and a correlation coefficient of 0.931 and 0.916 (RMSE=7.825 and 8.817) were achieved with support vector machines radial based and polynomial based approaches respectively.

To compare the performance of Support Vector Machines, a back propagation neural network based modelling approach was used. An Architecture performing well for both data sets is chosen after a large number of trials. The back-propagation neural network used for slump and strength

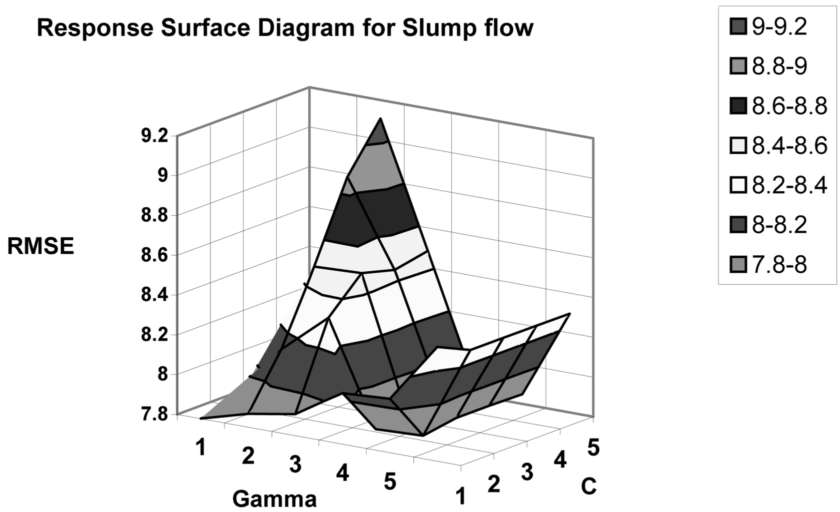

Fig. 8 Response Surface Diagram for Interaction between C and Gamma for Slump flow

prediction uses a learning rate of 0.3-momentum value as 0.2 and one hidden layer with six numbers of nodes; weights and biases were initialised randomly. Correlation coefficient and RMSE achieved by using neural network modelling approach for strength and slump prediction are given in table 3. A comparison of results obtained by Support Vector Machines and neural network approach suggest a comparable performance by both modelling approaches for both strength and slump prediction. Fig. 5 and Fig. 6 show the plot between the actual and predicted values of slump flow and 28-day compressive strength by neural network approach.

6. Conclusions

Results from this study suggested that Support Vector Machines modelling approach perform well in predicting both 28-day compressive strength and slump flow for the SCC data set used in present study. The optimum value of parameters *C, d* and γ were obtained as 20, 2 and 0.25 respectively, after a large number of trials by varying these values for different data sets used in present study. Further enhancement of model can be achieved by using new data developed during the actual designing of SCC mixtures. The SCC mixture can be designed as per specifications, and then presented to the Support Vector Machines model to predict its properties. The results obtained suggest that Support Vector Machines based approach can effectively be used to analyse the complex relationship between various parameters used in predicting the 28-day compressive strength and slump flow of self-compacting concrete as an alternative to neural network approach. It was observed that in comparison to neural network, Support Vector Machines approach requires less number of user-defined parameters to be set and also involves using a small computational cost, as choice of suitable architecture has always been a problem with neural network approach and requires lot of efforts and computational cost.

References

Bouzoubaa, N. and Lachemi, M. (2001), "Self-compacting concrete incorporating high volumes of class F fly ash Preliminary results", *Cement Concrete Res.*, **31**, 413-420.

Bui, V.K., Akkaya, Y. and Shah, S.P. (2002), "Rheological model for self-consolidating concrete", *ACI Mater. J.,* **99**(6), 549-559.

Chengju, G. (1989), "Maturity of concrete: Method for predicting early stage strength", *ACI Mater. J.,* **86**(4), 341-353.

Dias, W.P.S. and Pooliyadda, S.P. (2001), "Neural networks for predicting properties of concretes with Admixtures", *Constr. Build. Mater*., **15**, 371-379.

Dibike, Y.B., Velickov, S., Solomatine, D.P. and Abbott, M.B. (2001), "Model induction with support vector machines: Introduction and applications", *J. Comput. Civ. Eng.,* ASCE, **15**, 208-216.

Ghezal, A. and Khayat, K.H. (2002), "Optimizing self-consolidating concrete with limestone filler by using statistical factorial design methods", *ACI Mater. J.*, **99**(3), 264-268.

Hong-Guang, N. and Ji-Zong, W. (2000), "Prediction of compressive strength of concrete by neural networks" *Cement Concrete Res.,* **3**(8), 1245-1250.

Kasperkiewicz, J., Rach, J. and Dubrawski, A. (1995), "HPC strength prediction using Artificial neural network", *J. Compu. Civ. Engg.*, **9**(4), 279-284.

Kim, J.I., Kim, D. K., Feng, M.Q. and Yazdani, F. (2004), "Application of Neural Networks for Estimation of Concrete Strength", *J. Mater. Civ. Eng.,* **16**(3), 257-264.

Ji, T. and Lin, X.J. (2006), "A mortar mix proportion design algorithm based on artificial neural networks". Computers and Concrete, **3**(5), 357-373.

Lai, S. and Serra, M. (1997), "Concrete strength prediction by means of neural network", *Constr. Build. Mater*., **11**(2), 93-98.

Lee, S. (2003), "Prediction of concrete strength using artificial neural networks", *Eng. Struct*., **25**(7), 849-857.

Lee, J.J., Kim, D.K., Chang, S.K., and Lee, J.H. (2007), "Application of support vector regression for the prediction of concrete strength", *Comput. Concrete,* **4**(4), 299-316.

Nagamoto, N. and Ozawa, K. (1997), "Mixture properties of self-compacting, High performance concrete" *Third CANMET/ ACI International Conference on Design and Materials and Recent Advances in Concrete Technology, SP-172, V.M.Malthotra, ed., American Concrete Institute, Farmington Hills, Mich*., 623-627.

Nehdi, M., Chabib, H.E. and Naggar, M.H.E. (2001), "Predicting performance of self-compacting concrete mixtures using artificial neural networks" *ACI Mater. J.*, **98**(5), 394-401.

Oh, J.W., Kim, J.T. and Lee, G.W. (1999), "Application of neural networks for proportioning of concrete mixes", *ACI Mater. J.*, **96**(1), 61-67.

Okamura, H. (1997), "Self-compacting concrete-Ferguson Lecture for 1996", *Concr. Int.*, **19**(7), 50-54.

Oluokun, F.A., Burdette, E.G. and Deatherage J.H. (1990), "Early-age concrete strength prediction by maturity - Another look", *ACI Mater. J.*, **87**(6), 565-572.

Pal, M. and Mather, PM. (2003), "Support vector classifiers for land cover classification", *Map India 2003*, New Delhi, 28-31 January, www.gisdevelopment.net/technology/rs/ pdf/23.pdf.

Patel, R., Hossain, K.M.A., Shehata, M., Bouzoubaa, N. and Lachemi, M. (2004), "Development of statistical models for mixture design of high-volume fly ash self-consolidation concrete", *ACI Mater. J.*, **101**(4), 294-302.

Platt, J.C. (1999), "Fast training of support vector machines using sequential minimal optimization". *Advances in Kernels Methods: Support vector machines*, Schölkopf, B, Burges, C. and Smola, A. (Eds.), Cambridge, MA: MIT Press.

Popovics, S. (1998), " History of a mathematical model for strength development of Portland cement concrete". *ACI Mater. J.*, **95**(5), 593-600.

Ren, L.Q. and Zhao, Z.Y. (2002), "An optimal neural network and concrete strength modeling". *J. Adv. Eng. Software*, **33**, 117-130.

Sebastia, M., Olmo, I.F., and Irabien, A. (2003), "Neural network prediction of unconfined compressive strength of coal fly ash-cement mixtures", *Cement Concrete Res.,* **33**, 1137-1146.

Smola, A.J. (1996), "Regression estimation with support vector learning machines", Master's Thesis, Technische

Universität München, Germany.

Snell, L.M., Van Roekel, J. and Wallace, N.D. (1989), "Predicting early concrete strength", *Concrete Int.*, **11**(12), 43-47.

Sonebi, M. (2004a), "Application of statistical models in proportioning medium strength self-consolidating concrete" *ACI Mater. J.*, **101**(5), 339-346.

Sonebi, M. (2004b), "Medium strength self-compacting concrete containing fly ash: Modelling using factorial experimental plans", *Cement Concrete Res.*, **34**(7), 1199-1208.

Witten, I.H. and Frank, E. (1999), *Data Mining: Practical Machine Learning Tools and Techniques with Java Implementations*. Morgan Kaufmann, San Francisco.

Vapnik, V.N. (1995), *The Nature of Statistical Learning Theory,* Springer-Verlag, New York.

Yeh, I-Cheng. (1998a), "Modeling concrete strength using augment-neuron network", *J. Mater. Civ. Eng.*, **10**(4), Nov.

Yeh, I-Cheng. (1998b), "Modeling of strength of high-performance concrete using artificial neural networks", *Cement Concrete Res.,* **28**(12), 1797-1808.

Yeh, I-Cheng. (1999), "Design of high-performance concrete mixture using neural networks and nonlinear programming". , *J. Comput. Civ. Eng.*, **13**(1), Jan.

Yeh, I-Cheng. (2008), "Prediction of workability of concrete using design of experiments for mixtures". *Comput. Concrete,* **5**(1), 1-20.