Archives of Materials Science and Engineering
Volume 99
Issues 1-2
September-October 2019
Pages 30-41
International Scientific Journal published monthly by the World Academy of Materials and Manufacturing Engineering

DOI: 10.5604/01.3001.0013.5880

Estimating the compressive strength of concrete, using vacuum dewatering technique

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ABSTRACT

Purpose: Investigate the potential of vacuum dewatering process of on three different grades of concrete namely M20, M30 and M40 to evaluate its compressive strength.

Design/methodology/approach: For this study a data set of 90 experimental observations obtained from laboratory testing with and without application of vacuum dewatering after designing and casting the concrete of said three grades. The standard cubes of size 150 mm × 150 mm × 150 mm were obtained by core cutting and tested for compression after 3, 7, 14, 21 and 28 days of proper curing. Accuracy of prediction of compressive strength of concrete by application of M5P, ANN and SVM as artificial intelligence techniques and their feasibility are assessed to estimate the compressive strength of the concrete enacted with vacuum dewatering technique. A total data set was segregated in two groups. A group of 63 observations was used for model development and smaller group of 27 observations was used for testing the models.

Findings: Overall performance of ANN based developed model is better than M5P and SVM based models for predicting the compressive strength of concrete for this data set.

Research limitations/implications: Investigated three different grades of concrete namely M20, M30 and M40 to evaluate its compressive strength. The experimental research involved only testing of cubes only.

Practical implications: Using ANN based developed model makes it possible to quickly and accurately predict the compressive strength of concrete.

Originality/value: The results of comparing three models for predicting the compressive strength of concrete and the optimal values of ANN based developed models are presented. Earlier no one has applied M5P, ANN and SVM modelling to predict the compressive strength of vacuum dewatered concrete.

Keywords: Vacuum dewatering, Concrete compressive strength, Artificial Neural Network, Support Vector Machine

Reference to this paper should be given in the following way:

D. Subhash, S.M. Gupta, S. Setia, V. Pavlykivskyi, Estimating the compressive strength of concrete, using vacuum dewatering technique, Archives of Materials Science and Engineering 99/1-2 (2019) 30-41.

METHODOLOGY OF RESEARCH, ANALYSIS AND MODELLING

1. Introduction

Vacuum dewatering is an innovative technique of concrete construction which allows high water cement ratio to facilitate the mixing process and improve its workability to enable it to be handled, placed into complicated mould or around over and extensive reinforcement with full compaction. After placement, the concrete is subjected to a vacuum dewatering process to extract the excess water, needed for workability only and no longer required for the freshly placed concrete. Vacuum dewatered concrete is especially used for slabs and floors, was first invented by Billner in the United States of America in 1935 [1]. Concrete is vacuum treated by placing a filter pad over the freshly cast and compacted surface to prevent cement particles passing through it. An air tight suction mat is placed over the filter pad, with a hose connecting the suction mat to the vacuum pump. When vacuum pump is operated, creates a differential pressure between the concrete and outside air, causes a uniform downward pressure of about 0.08 MPa on the upper surface of the concrete [2]. Vacuum dewatering process squeezes out the excess from the concrete, causes its compaction due to mobilization of atmospheric pressure acting on the surface of the concrete created by vacuum. The extracted water carries away 0.2 to 0.5 percent of cement fine, filter pad minimize the loss of cement fines [3].

The vacuum dewatering technique therefore lowers the final water cement ratio of freshly placed concrete by 15 to 25 percent before its setting [4]. The technique produces concrete with better mechanical and physical properties like higher strength and abrasion resistance, reduce shrinkage and permeability and increases durability than would otherwise be obtained [5-8]. The literature shows that the required vacuum time is 2 to 5 minutes per 25 mm thickness and found effective only for upper 150 mm of fresh concrete [9]. Vacuum dewatering cannot extract water desired for hydration because the capillary diameters in cement matrix decreases as the water- cement ratio decreases [10]. Thus, there is no problem that the water cement ratio will fall below 0.30, which will above the minimum water cement ratio required for the hydration of the cement. Research also reports that permeable and absorbing form work are other recent methods of reducing water cement ratio of concrete after casting which is conceptually similar to vacuum dewatering but it is found effective to a depth of 25 to 50 mm [11]. Rubaratuka's investigation shows an increase of compressive strength and other parameters influenced by absorbing form work [12]. It is also observed that vacuum dewatering of bending element (slabs) delays the appearance of first crack and reduces crack width at every stages of loading accompanied with increase of bending strength [13]. The application of said technique can save more than 15 percent of cement with no effect on the properties of concrete. It also improves the imperviousness against organic fluids etc. [14].

Experimental study of compressive strength of concrete is very time and resource consuming process, as for many others process [15,16]. To economize the phenomena, various numeric techniques evolved and give an alternate approach to forecast the compressive strength of the concrete. Numerical methods are a very universal tool for scientific research [17-19]. These techniques accompanied with software applications give rise to the numerous algorithm based modelling tools like ANN, M5P, Random Forest, adaptive neuro fuzzy inference system and SVM etc. to resolve complex civil engineering problems [20]. To the best of author's knowledge no one has applied M5P, ANN and SVM modelling to predict the compressive strength of vacuum dewatered concrete. The main purpose of this study is to forecast the compressive strength of concrete subjected to vacuum dewatering technique by taking different ingredients like water-cement ratio, quantity of cement, admixture and slump etc. as the variables after processed by M5P, ANN and SVM [21,22].

2. Materials and methods

2.1. Soft computing techniques

M5P model tree

M5P model tree is a soft computing tool, introduced by Quinlan in 1992 for regression problems [23]. This model tree algorithm designates one-dimensional function on the end nodes which anticipate continuous numerical abstracts. It is a tree based modelling made on the principle of division and subduing. This generation of tree based modelling needs two continuous parts for processing the input data. The initial part of the model split the total input data into numbers of subclasses and thus forming a decision tree. Considering the standard deviation of class values after testing the abstract at the node of that branch forms the base of M5P tree algorithm. Referring (Quinlan-92), every successive node of information contains less error or standard deviation than that of its preceding node after processed with division operation. After permuting all the possible divisions, M5P select the best model which decreases the error to the minimum possible level after testing every abstract at that node. The issue of division of data set sometime introduces over fitting due to development of large tree like structures. To address this issue, model tree needs to be trimmed off. The job of trimming off the oversized model tree performed in second stage by replacing sub trees with linear regression functions.

Artificial Neural Network

ANN is a computing system, using artificial intelligence, applies some functions of animal brain. ANN models are numerical tools capable of predicting the solution after assessing the complex civil engineering problems [24]. ANN computes and operates on the basis of group of interconnected nodes, taken as artificial neurons which form the different layers namely input, hidden and output layers. The connectionist system between numbers of nodes in different layers marks the weighted association between them. The input layer consists of units related to input parameters. It does not process the data. The hidden layers(s) follows input layer to process the data and in turn communicate the data to the output layer to process it finally [25]. ANN implies random function probabilistic tool by taking sample of data out of entire observed data sets to reach at final solution by saving the resources and become one of the most economical soft computing technique to predict the compressive strength of concrete and engineering problems [26].

Support Vector Machine (SVM)

Support Vector Machine, a soft computing technique, based on decision vector also known as support vector, gives the title to the technique which limits the data as a learning algorithm. The decision vector classifies the data into different labels present in the data set. Decision vector is a linear classifier. Although, it is a controlled learning algorithm and maybe applied to analyse the regression and classification problems but found very handy for classification challenges. In this supervised machine learning, each parameter of data item is taken as point in a space, having dimensions as per number of parameters. Different class of data is classified by choosing decision vector or hyper plane as per the dimension(s) of data feature. The selection of the right decision vector or hyper plane to segregate the different types of data is that which present the different class of data at maximum distance from the best decision vector or hyper plane. The distance is defined as the margin. The class of data is misclassified if decision vector or hyper plane has low margin. Support Vector Machine has got an advancement to ignore the data which out lies from its class to select the decision vector or hyper plane to have the maximum margin. So SVM is a robust in such situations. SVM is very useful tool to produce an intelligent system to make models for data processing in variety of civil engineering problems [27]. As, lot of modelling techniques have been emerged to simulate different structural engineering data. The compressive strength of concrete, forecast by using SVM models go well with experimental observations [20]. In this research authors attempted to apply Support Vector Machine for simulating the observed data on compressive strength of vacuum dewatered concrete and forecast the compressive strength for changed ingredients as experimental method is very resource consuming.

2.2. Experimental program

Material and mix proportions

Ordinary Portland cement, 43 grades (OPC43), from a single source has been used throughout the investigation. The physical properties of cement confirmed to IS-8112:1989 [28] and tested as per the recommendations of IS-4031:1988 [29]. Locally available river sand having specific gravity 2.61 and fineness modulus of 2.63 was used as fine aggregate. The fine aggregate confirmed to zone 2 of IS-383:1970 [30]. A well graded crushed stone was used as a coarse aggregate of maximum size 20 mm and minimum size of 10 mm fulfilling the relevant Indian standard specifications. In this research study, the basic guidelines and specifications for mix proportioning were followed in accordance with IS-10262:2009 [31] and IS-456:2000 [32]. A number of trials mixes for three different grades of concrete M20, M30 and M40 were prepared and examined to carry out the selection of appropriate proportions of different ingredients i.e. cement, fine aggregate, coarse aggregate, water and plasticizer etc. [33], fulfilling the desired objectives in term of strength and workability. The details of the different ingredients used for proportioning and designing for three grades of concrete mixes M20, M30 and M40 are given below in Table 1.

Casting of specimen

Fabricated steel moulds of size 1500 mm × 1500 mm × 150 mm were used to cast the concrete slabs for M20, M30, and M40 concrete mixes with and without vacuum dewatering. The process of vacuum dewatering was carried out for 30 minutes and about 17 %, 15 % and 12 % of the water, added at the time of mixing was sucked out from M20, M30 and M40 grade of concrete mixes respectively. The slabs were cured properly and forty five numbers of concrete cubes of standard size 150 mm × 150 mm × 150 mm were obtained by core cutting from each slab using three grades of controlled concrete mixes M20, M30 and M40.

Table 1.
The details of the various ingredients used for proportioning and designing for three grades of concrete mixes M20, M30 and M40

Sr. No.	Constituents	Mix designation		
		M20	M30	M40
1	Cement, kg	382.75	410	430
2	Fine Aggregate, kg	715	710.35	718.1
3	Coarse Aggregate, kg	758.28 (20 mm) 408.30 (10 mm)	759.30 (20 mm) 408.8 (10 mm)	722.40 (20 mm) 388.90 (10 mm)
4	Water, Ltr.	191.38	184.50	184.90
5	Water cement ratio	0.50	0.45	0.43
6	Plasticizer by weight of cement, Ltr.	1.91	2.05	2.15
7	Proportions	1:1.87:3.05	1:1.73:2.85	1:1.67:2.71

Table 2.
Compressive strength values for controlled and vacuum dewatered concrete at different curing period

Sr. No.	Curing time (No. of days)	Compressive strength, MPa					
		M20		M30		M40	
		Controlled	VDC	Controlled	VDC	Controlled	VDC
1	3	14.85	23.50	20.90	32.53	26.40	40.53
2	7	21.15	30.90	30.06	43.30	37.90	53.53
3	14	23.50	33.40	33.40	47.13	42.13	58.03
4	21	25.53	36.30	36.60	49.80	46.10	62.17
5	28	27.60	38.40	39.20	53.30	49.40	65.16

The same procedure was adopted after vacuum dewatering, to obtain again forty five numbers of the cubes from the above said concrete mixes. All the specimens were obtained by core cutting were kept with proper curing until these were tested.

Testing program

The compressive strength of the concrete is most important property as it also signifies other parameters like hardness, flexural, split tensions and durability etc. So, all the cubes were tested in this study as per IS516:2004 [34] in a compression testing machine which was of capacity of 250 ton was of a reliable type and recently calibrated. The tests were conducted at the ages of 3, 7, 14, 21 and 28 days on the specimens of M20, M30 and M40 grades of controlled and vacuum dewatered concrete. All specimens were tested immediately after removal from water tank and were still in moist condition. The surface water and grit were wiped off and all projecting fines were removed from the specimens. The results shown below in Table 2 are averages of three specimens from each class of controlled and vacuum dewatered concrete at the ages mentioned against them. The observations which were outlying were ignored.

2.3. Modelling program

Data set

Data sets with 90 numbers of experimental observations obtained from the experimental setup were used. Out of total 90 numbers of observations 63 numbers were used for training and remaining 27 numbers were used to test the model (Tab. 3). The input data sets are consisting 3 numbers of different concrete mixing; M20, M30 and M40 and water cement ratio 50%, 45% and 43% and 382.35 kg, 410 kg and 430 kg of cement were used respectively. 715 kg, 710.35 kg and 718.1 kg of fine aggregate and 758.28 kg, 759.3 kg and 722.4 kg of course aggregate of maximum size 10 mm and 408.3 kg , 408.8 kg and 388.9 kg of coarse aggregate of maximum size of 20 mm along with 1.91 kg, 2.05 kg and 2.15 kg admixture were used respectively for three different grade of concrete mixes. Workability of 123 mm, 109 mm and 104 mm of slump were observed respectively. The compressive strength was observed after curing of 3, 7, 14, 21 and 28 days respectively.

Table 3.
Features of the dataset used for modelling

Approaches	Minimum	Maximum	Mean	Standard Deviation	Skewness
			Training data +BA3:BE28set		
C	382.75	430	407.5833	19.52082	-0.1898
W/C	0.43	0.5	0.46	0.029676	0.481881
Fa	710.35	718.1	714.4833	3.21053	-0.24493
CA1	722.4	759.3	746.66	17.29729	-0.72255
CA2	388.9	408.8	402	9.339769	-0.72289
Ad	1.91	2.15	2.036667	0.099223	-0.20563
Wk	104	123	112	8.106151	0.520139
T	3	28	14.68254	9.154279	0.188877
P	1	2	1.507937	0.503953	-0.03253
CS	14.4	65.7	38.35794	13.01088	0.336661
			Testing data set		
C	382.75	430	407.5833	19.73417	-0.19633
W/C	0.43	0.5	0.46	0.03	0.498462
Fa	710.35	718.1	714.4833	3.245618	-0.25336
CA1	722.4	759.3	746.66	17.48634	-0.74741
CA2	388.9	408.8	402	9.441846	-0.74776
Ad	1.91	2.15	2.036667	0.100307	-0.2127
Wk	104	123	112	8.194745	0.538037
T	3	28	14.40741	9.282984	0.173266
P	1	2	1.481481	0.509175	0.078558
CS	14.9	62.8	37.47222	12.22315	0.235171
			Total data set		
C	382.75	430	407.5833	19.47377	-0.1884
W/C	0.43	0.5	0.46	0.029604	0.47834
Fa	710.35	718.1	714.4833	3.20279	-0.24313
CA1	722.4	759.3	746.66	17.2556	-0.71724
CA2	388.9	408.8	402	9.317255	-0.71758
Ad	1.91	2.15	2.036667	0.098984	-0.20412
Wk	104	123	112	8.08661	0.516317
T	3	28	14.6	9.141583	0.180908
P	1	2	1.5	0.502801	1.79E-17
CS	14.4	65.7	38.09222	12.71773	0.312782

3. Result and discussion

3.1. Experimental results

The present study was undertaken to explore the potential advantages accruing from the use of vacuum dewatering technique for concrete construction. To this end, the behaviour of controlled and vacuum dewatered concrete in compression has been investigated experimentally. Results of cube strength of specimens of contemporary controlled and vacuum dewatered concrete at different ages of curing were compared and analysed. It was found that the early compressive strengths of vacuum dewatered concrete were about 60%, 57% and 54% higher than that of controlled concrete of M20, M30 and M40 concrete mixes respectively. The corresponding increases of 28 days compressive strength of vacuum dewatered concretes were about 40%, 36% and 32% than that of controlled concretes. The water taken out by vacuum dewatering was about 17%, 14% and 12% for M20, M30 and M40 grades of concrete mixes respectively. It is also observed that the more the water sucked out the better the increase of compressive strength of vacuum dewatered concrete. Figure 1, given below shows the comparison of the compression strength of controlled and vacuum dewatered concretes for different concrete mixes along the age of curing, undertaken in this study.

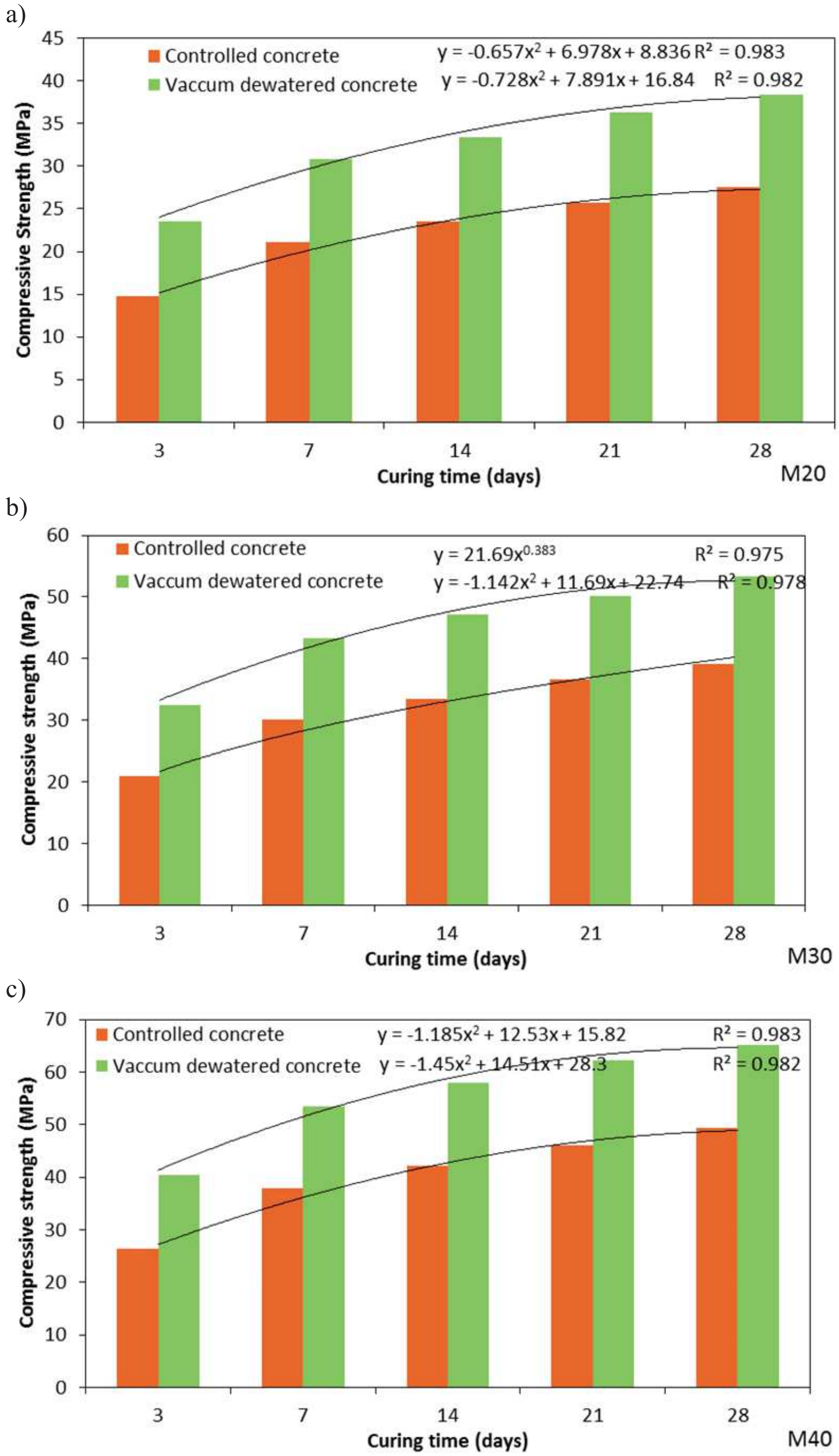


Fig. 1. Compressive strength of controlled and vacuum dewatered concrete for different curing periods and various mix design: a – concrete grade M20; b – concrete grade M30; c – concrete grade M40

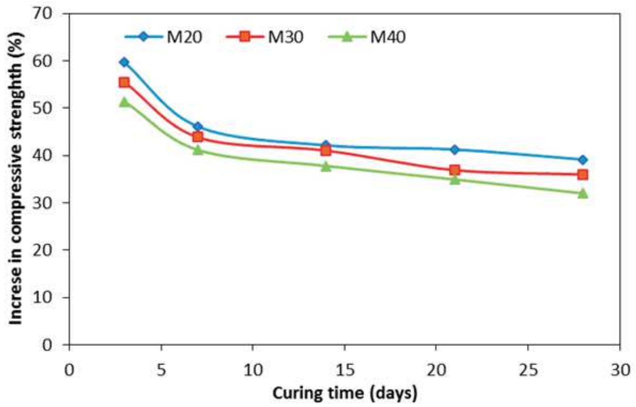


Fig. 2. Percentage increase of compressive strength of vacuum dewatered concrete compared with the controlled concrete for different mix design

Figure 2, shows the comparison of the percentage increase of compressive strength of vacuum dewatered concrete compared with the controlled concrete along the time of curing for M20, M30 and M40 concrete mixes undertaken in this study.

3.2. Modelling results

Goodness of fit parameters coefficient of correlation (CC), root mean squared error (RMSE) and Mean absolute error (MAE) values were implemented for the evaluation of performance of developed models. A large number of manual trials were carried out to find the values of primary parameter of developed models. The primary parameters selected for the modelling technique are shown in Table 4.

Table 4.
Optimum values of primary parameters selected for various modelling techniques

S. No.	Machine learning approach	Primary parameters
1	M5P	m =4
4	SVM-RBF	C=2,γ=2
5	SVM-PUK	C=2, ω=1, β=1
6	ANN	structure: 4-4-1 learning rate: 0.2 momentum: 0.1 iteration: 1500

Results of M5P models

Model development is a trial and error process. The optimal value of m is found 4 for model development. Figure 3 shows the plot among actual and predicted values of compressive strength of concrete (MPa) for training and testing stages. The results of performance evaluation parameters were listed in Table 5. The M5P Based model has attained CC = 0.9823 and 0.9791, RMSE = 2.4172 and 2.4662 (MPa) and MAE = 1.9858 and 2.0484 (MPa) for training and testing stages respectively. Overall performance of M5P based developed model is satisfactory for predicting the compressive strength of concrete for this data set.

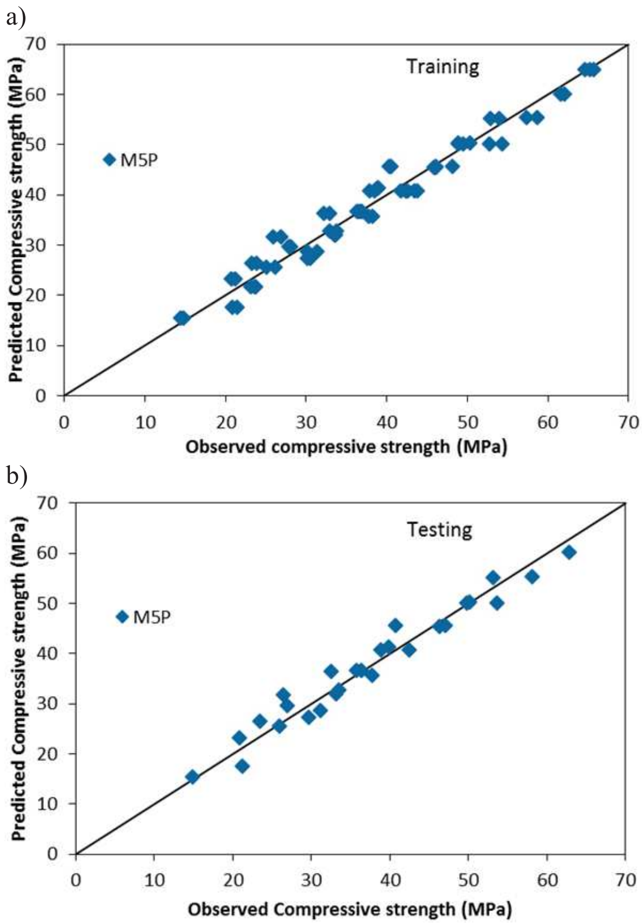


Fig. 3. Performances of M5P model at different stages: a – training stage; b – testing stage

Results of SVM models

SVM model development is similar process as M5P model development. The optimal value of SVM based developed models are listed in Table 4. Figure 4 shows the plot among actual and predicted values of compressive strength of concrete (MPa) using SVM based models for training and testing stages. The results of performance evaluation parameters for training and testing stages were listed in Table 5. Figure 4 and Table 5 suggest that SVM_PUK works better than SVM_RBF based models for predicting the compressive strength of concrete. Overall performance of SVM based developed model is better than M5P based model for predicting the compressive strength of concrete for this data set.

Table 5.
Performance evaluation parameters for M5P, SVM and ANN

Approaches	Training dataset			Testing dataset		
	CC	RMSE	MAE	CC	RMSE	MAE
M5P	0.9823	2.4172	1.9858	0.9791	2.4662	2.0484
SVM_RBF	0.9947	1.3768	0.8250	0.9936	1.4138	1.0071
SVM_PUK	0.9991	0.5496	0.3574	0.9988	0.6206	0.5301
ANN	0.9989	0.6468	0.5266	0.9989	0.6345	0.4766

a) b)

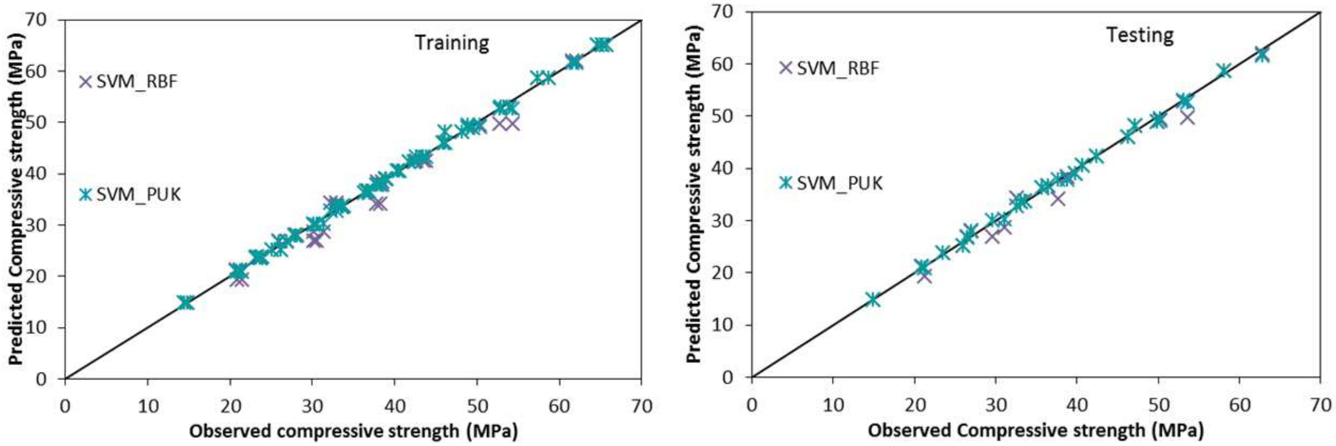


Fig. 4. Performances of SVM model at different stages: a – training stage; b – testing stage

a) b)

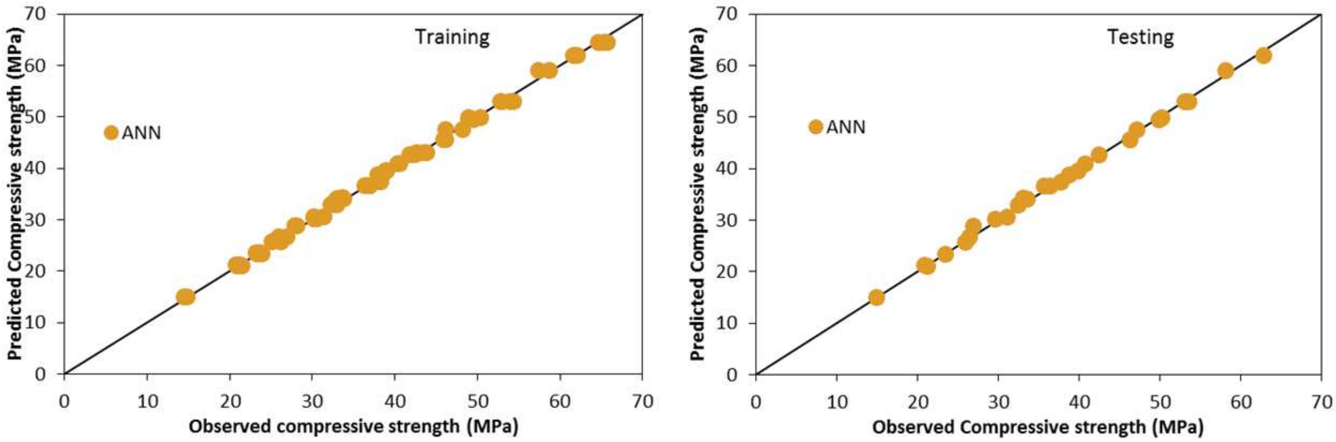


Fig. 5. Performances of ANN model at different stages: a – training stage; b – testing stage

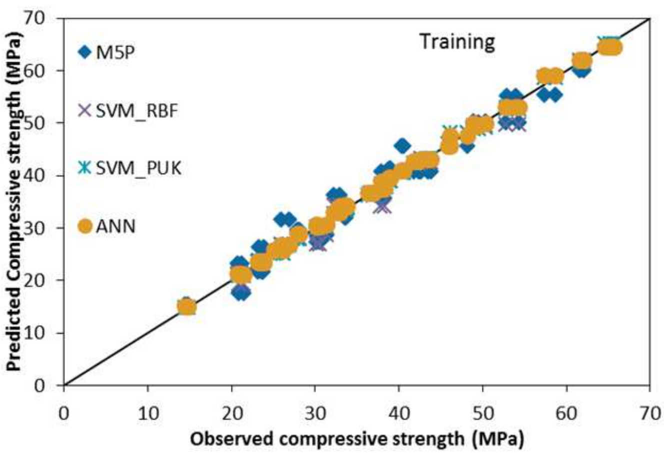
Results of ANN

ANN model development is also as similar process as M5P and SVM based model development. The optimal value of ANN based developed models are listed in Table 3. One hidden layer is used in this study for the model development. Figure 5 shows the plot among actual and predicted values of compressive strength of concrete (MPa) using ANN based models for training and testing stages. The results of performance evaluation parameters for training and testing stages were listed in Table 5. Overall performance of ANN based developed model is better than M5P and SVM based models for predicting the compressive strength of concrete for this data set.

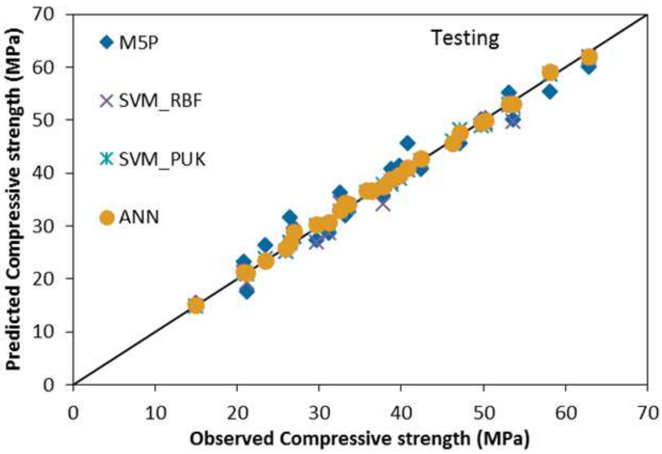
Comparison of the developed models

This section indicates the comparison among M5P, SVM and ANN based model for predicting the compressive strength of concrete. Figure 6 shows the agreement and error plot using M5P, SVM and ANN based model for predicting the compressive strength of concrete for both training and testing stages respectively. Figure 6 indicates that the values obtained by ANN based model has closed to line of perfect agreement with lesser error than other discussed models. Overall performance of ANN based developed model is better than M5P and SVM based models for predicting the compressive strength of concrete for this data set.

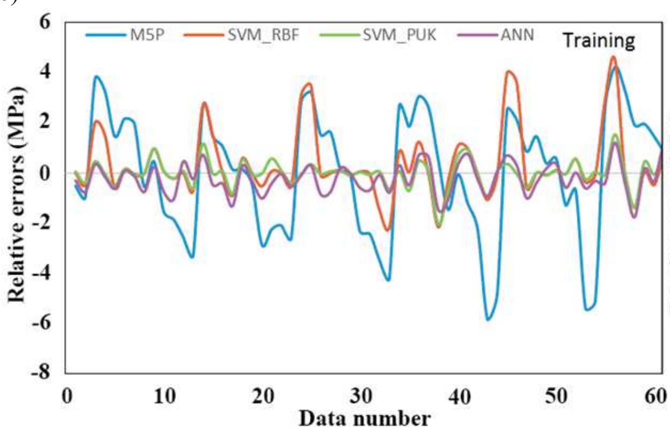
a)



b)



c)



d)

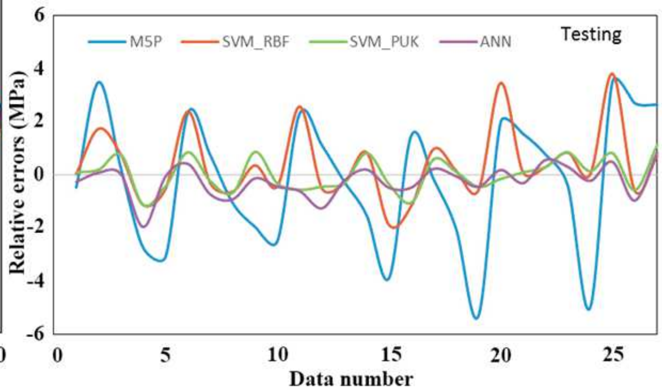


Fig. 6. Performances of M5P, SVM and ANN in different stages of model development and testing: a – actual and predicted values of compressive strength of concrete for training stage; b – actual and predicted values of compressive strength of concrete for testing stage; c – relative errors for training stage; d – relative errors for testing stage

4. Conclusions

The present investigation was undertaken to explore the potential advantages, accruing out of the application of vacuum dewatering as construction technique. The structural performance of concrete mainly depends upon its strength in compression. So, cubes of concrete were tested to observe the compressive strength of specimens of three different grades of concrete M20, M30 and M40 for controlled and vacuum dewatered concrete. This has entailed into experimentation of more than 90 specimens inhabiting cubes, obtained by core cutting. The experimental results were then processed for prediction by using different soft computing techniques and documentation of vacuum dewatering technique based concrete.

On the basis of experimental investigations and analysis of results/observations obtained, the following conclusions may be drawn broadly.

1. The application of vacuum dewatering technique gives a freedom to use as much of water cement ratio as required for desired workability without inducing any adverse effect on the performance of hardened concrete.
2. The effect of the technique on early compressive strength of the concrete was found very significant. The early increase in strength was of the order of about 60%, 57% and 54% for M20, M30 and M40 grades of concrete mixes respectively. So, formwork and shuttering may be removed earlier and working time is also reduced. It all results in cost optimization of concrete construction.
3. The increase in 28 days compressive strength was observed about 40%, 36% and 32% for M20, M30 and M40 grades of concrete mixes respectively. Being this an appreciable increment of compressive strength if taken in account in the design, the thickness/size of the element will be reduced, the application technique was found very useful.
4. The results obtained, using artificial intelligence techniques view that ANN based computing model delivers and evident for appropriate approaches to predict the compressive strength of the concrete as it gives better performance, almost close to the line of perfection with lesser error than M5P and SVM computing models.

5. Scope for further study

Based on the conclusion drawn and also keeping in view the limitation of the present study, the following scopes are suggested for future research in order to supplement the present information:

1. The validity of above said conclusions can be explored for wider range of variables i.e. concrete mixes, water/cement ratio and for different curing conditions and periods etc.
2. The experimental research reported here involved only testing of cubes only, therefore it will be interesting to study the behaviour of full sized beam and slab elements etc.
3. It would be very interesting to explore the effects of said technique on prism, cylinder for flexural and split tensile strength and may be applied on the fibre based concrete which is an advance generation of concrete; as the use of steel fibres addresses the tensile and other weaknesses of concrete.
4. In the present study to predict the compressive strength M5P, SVN and ANN were used as soft computing techniques but same may be assessed by using other established artificial intelligent based techniques.

Acknowledgements

The authors' team is grateful to the administration of the NIT Kurukshetra for the opportunity to conduct scientific research.

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