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Research paper

Principal component analysis for concrete mix by ranking method

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Abstract

Cement concrete mixture design for pavement was studied through a series of laboratory experiments based on an actual project program. The main purpose of this research is to investigate the minimum cement content required with an appropriate water-cement ratio (w/c) to meet given workability, strength, and durability requirements in a concrete pavement; and to reduce costs. An experimental program was conducted to test [9] concrete mixtures, designed according to Taguchi's orthogonal selection with w/c of 0.36, 0.45 and 0.55 and cured by different methods such as Air Curing (AC), Water Curing (WC) and Plastic Bag Curing (PBC) separately. Compressive strength (CS) of 150mm cubes are found for [3-7] and14 days. Cube compressive strength, water to cement ratio (w/c), Cement, Coarse Aggregate, Fine Aggregate were the parameters to be used for optimization by varying water-cement ratios, cement quantities, Coarse Aggregate (CA) quantities and Fine Aggregates (FA) quantities. The data sets of mix designs were analyzed by Principal Component Analysis (PCA) to draw most influencing variables on the performance of concrete. From the analysis, it is found that w/c is the most influencing ingredient in case of AC and PBC and CA for WC on Compressive Strength of concrete.

Keywords: *Cement Concrete; Water-Cement Ratio; Compressive Strength and Principal Component Analysis*

1. Introduction

Concrete is a heterogeneous material, composed of aggregates, cement, water and voids. In general, the quality and durability of the concrete depends on the amount of voids in concrete, called capillary voids. There is a strong correlation between the amount of voids in concrete and strength/permeability. It shows that, as the ratio of solid to void increases, strength increases and permeability improves. The voids in concrete, except for entrained and entrapped air, are created as the volume initially occupied by water is vacated as the water is consumed during the hydration process. Voids initially occupied by water in concrete are filled with hydrated gel.
As long as these voids are sufficiently filled with hydration products, the quality of concrete will be maintained at a satisfactory level. Curing is one of the influencing factor on which the hydration process depends. It is not possible; to cure the concrete only with water. The strength of the concrete depends on many factors such as mix proportion, type of curing and duration of curing.
So, it is necessary, to optimize the concrete mix for better results; also to know the strength variations in different for different types of curing and the most influencing variable on concrete.

2. Literature survey

Principal component analysis (PCA) is an old and popular technique in multivariate analysis and is very versatile. It operates in an unsupervised manner and is used to analyze the inherent structure of the data. It is chiefly used for dimensionality reduction of the data set by finding an alternate set of coordinates, known as the principal components.
PCA is a scientific method of quantitative analysis and is preferred over traditional visual analysis methods, when many factors are considered. However this method is not reliable when the contribution of the first and second principal components does not reveal much. In such cases, other methods need to be considered (Lianjie Niu et al. 2013).
PCA can also be interpreted as a neural network model. In addition to CA, covered in this paper, generalized PCA can also be shown to incorporate a very large set of multivariate techniques such as canonical variate analysis, linear discriminant analysis and bar centric discriminant analysis techniques such as discriminant CA (Herve´ and Lynne 2010).
PCA was applied to field data collected from a two-lane highway section in the state of Tripura, India. (Pritam Sahaa et al. 2006) as a pre-processing step prior to clustering. The data displayed lot of heterogeneity. Spearman's rank correlation test showed that there is a high correlation between PCA and Data Envelopment Analysis (DEA) ranking values for this data set (Markus Ringnér 2008).
In evaluating the shear strength of the SFRC beams, Principal component regression models performed well for the existing equations and also for the multivariate regression model (Mohammad and Shahria 2013). Principal components analysis was used for Correlation of clusters for grouping of variables and identification of related variables (Calabrese et al. 2010). The impact of a crack which represents a good indication to detect abrupt change on their norms can be found easily using PCA components (Nicolas Stoffels 2014).PCA can condense subjective factors in IR thermography feature judgement to provide precise judgement and detection (An Ning et al. 2015).

ANN models are used for the purpose of optimization of ingredients of the concrete considering Water-cement ratio, maximum sand size, amount of gravel, cement, 3/4 sand, 3/8 sand, and coefficient of soft sand as inputs (Mehdi Nikoo 2015). Experimental results from different papers and reports were collected in a database in which slump flow test, V-funnel, L-box and J-ring are considered as parameters that was analyzed using data mining and multivariate analysis techniques. This technique is a comprehensive tool for an organized approach for assessment of the fresh state performance of SCC mixes (Emilio and Jose 2016). Principal Component Analysis reduces the dimensionality of the measured input data, thus decreasing the computation time of the Artificial Neural Networks (Potdar et al. 2015). Sparse PCA can be directly applied on analyzing multivariate time series as if the data are i.i.d. generated, by treating the transition matrix as a nuisance parameter (Zhaoran 2013).

3. Design concrete mix by taguchi model

In the present research, the concrete is designed for M40 initially and the parameters of concrete design are water, cement, Coarse Aggregate and Fine Aggregate. Each parameter is having with levels for optimization of parameters which are shown in Table 1

Table 1: Parameters and Levels

Specifications	Water	Cement	CA	FA
Level 1	176	320	1020	786
Level 2	176	392	1004	743
Level 3	176	488	1009	659

Based on the Taguchi orthogonal selection for four parameters and three levels an L9 Orthogonal array should be selected. An array for four controllable parameters is used to construct the matrix of three levels of controllable factors. Minitab is used to generate the necessary fraction of experiments out of whole set of experiments possible with four factors at three levels and the levels are shown in Table 2.

Table 2: Experimental Inputs Based on Factorial Method

Run number	Water	Cement	CA	FA
1	176	320	1020	786
2	176	392	1004	743
3	176	488	1009	659
4	176	320	1004	659
5	176	392	1009	786
6	176	488	1020	743
7	176	320	1009	743
8	176	392	1020	659
9	176	488	1004	786

3.1. Materials

The following materials were used in this investigation and properties of materials are shown in the Table 3 & Table 4.

Table 3: Properties of Cement

S. No.	TEST	RESULT	As per IS: 12269-1987 (RA 2008)
1	Normal Consistency	28.0 %	Not specified
2	Initial Setting Time	115 Min	> 30 Minutes
3	Final Setting Time	345 Min	< 600 Minutes
4	Compressive Strength (28 days)	53.0 Mpa	>53 Mpa
5	Fineness	310 m²/kg	>225 m²/kg
6	Soundness	0.5 mm	< 10 mm

Table 4: Properties of Fine and Coarse Aggregate

S. No.	Property	FA	CA
1	Specific Gravity	2.55	2.60
2	Fineness Modulus	2.74	3.16
3	Water Absorption	1.78	0.38

3.2. Preparation, curing and testing of specimen

Concrete cube specimens of size 150 mm were cured by AC, WC and PBC and used to determine the CS of Concrete mixes which are obtained from Taguchi's model as per (IS 516-1959, p.11) for 3, 7 and 14 days. Casting, Curing and Testing of Specimens cured by PBC are shown in Fig.1.The test results are shown in Table 5.

Fig. 2: Casting, Curing and Testing of Specimens Cured by PBC.

3.3. Consistency

At all times between mixing and discharge, the slump shall be within the range specified for the nominated mix mechanically placed or hand placed concrete. The consistency of the concrete shall be checked by use of a slump cone in accordance with AS 1012.3.1. The test shall be made on concrete samples obtained in accordance with AS 1012.1.

4. Results and discussions

Concrete cubes are cured for AC, WC and PBC and then tested for 3days, 7days and 14days.

Table 5: Compressive Strengths of Air, Water and Plastic Bag Curing Conditions

Mix	AC (3d)	AC (7d)	AC (14 d)	WC (3d)	WC (7d)	WC (14 d)	PBC (3d)	PBC (7d)	PBC (14 d)
M1	17.29	19.11	22.44	18.66	21.78	24.89	17.96	18.67	21.11
M2	19.33	21.55	23.33	20.22	29.56	31.08	23.11	24.89	28.89
M3	28.89	38.44	39.98	35.11	41.55	47.07	28.00	37.78	42.66
M4	25.33	26.44	29.55	29.33	32.22	40.22	26.67	28.44	32.44
M5	26.67	28.44	30.44	29.99	32.66	35.70	27.33	29.33	31.78
M6	30.89	33.97	37.29	32.67	39.78	42.89	32.22	37.11	40.18
M7	17.96	20.94	25.78	18.89	22.22	26.22	20.67	21.78	25.55
M8	22.67	26.67	28.89	28.00	30.89	39.56	26.89	28.89	31.56
M9	28.40	38.94	40.44	33.55	40.22	44.44	30.22	36.67	42.00

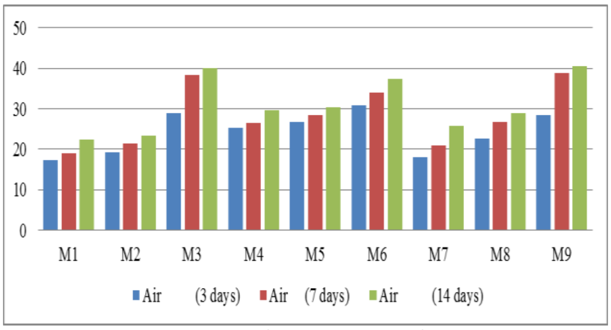

Fig. 2: Compressive Strengths of Concrete Mixes for Air (3, 7 & 14 Days) Curing.

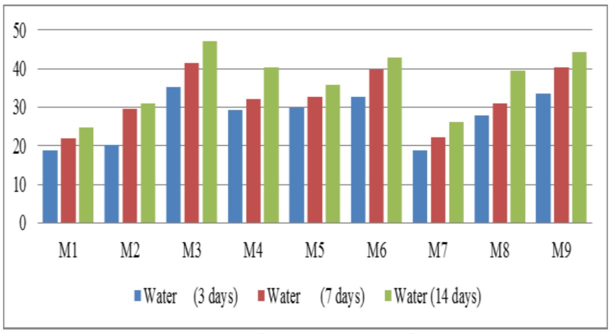

Fig. 3: Compressive Strengths of Concrete Mixes for Water (3, 7 &14 Days) Curing.

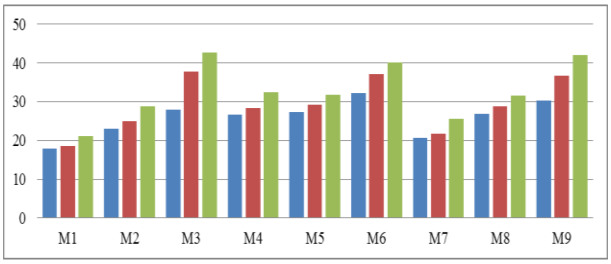

Fig. 4: Compressive Strengths of Concrete Mixes for Plastic Bag (3, 7 &14 Days) Curing.

In the present investigations, Concrete mixes are designed for M40 grade for w/c 0.36, 0.45 and 0.55 as per IS 10262-2009 and IS 456-2000. Taguchi method is uses a special design of Orthogonal arrays to study the entire process parameter with only a small number of experiments. Concrete mixes of three combinations of each w/c were obtained from Taguchi model. Concrete cubes of 150 mm of cubes all mixes were cast and cured by AC, WC and PBC methods. Then, the concrete mixes are tested for CS for 3, 7 and 14 days. The results are shown in Table 5, Fig. 2, Fig. 3 and Fig.4. It observed that Concrete mixes with w/c 0.36 exhibiting good strength for all types of curing for all days when comparing with the remaining mixes. It is also observed that CS of all concrete mixes showing higher CS for WC. Most of the cases of AC, Concrete mixes exhibit lower Compressive strengths.

5. Principal component analysis

Principal Component Analysis was conducted datasets of ingredients of concrete and Compressive Strength of Concrete for 14 days based on the curing method. The simulation runs was performed by MINITAB and MATLAB programs

5.1. Eigen analysis

After standardization of data sets, Covariance is calculated since many data sets have more than one dimension, and the aim of the statistical analysis of these data sets is usually to
see if there is any relationship between the dimensions. It is useful to find out how much the dimensions vary from the mean with respect to each other.

5.1.1. Air curing

Eigen vectors and their corresponding Eigen values were calculated and values are shown below Table 6 and Table 7 for AC respectively. Fig. 5 explained PCs versus Eigen Values whereas the relation between First and Second PCs are shown in Fig. 6 for Air Curing.

Table 6: Eigen Analysis of the Correlation Matrix (AC)

Eigen Value	2.7991	1.0246	1.0000	0.1725	0.0038
Proportion	0.560	0.205	0.200	0.034	0.001
Cumulative	0.560	0.765	0.965	0.999	1.000

Table 7: Eigen Vectors of the Correlation Matrix (AC)

Variable	PC1	PC2	PC3	PC4	PC5
w/c Ratio	0.581	-0.112	0.000	0.485	-0.644
Cement	-0.590	0.107	-0.000	-0.270	-0.754
Coarse Agg	0.038	0.630	0.766	0.121	0.016
Fine Aggregate	0.046	0.751	-0.642	0.145	0.019
f_{ck} (14 days)	-0.558	-0.125	0.000	0.810	0.129

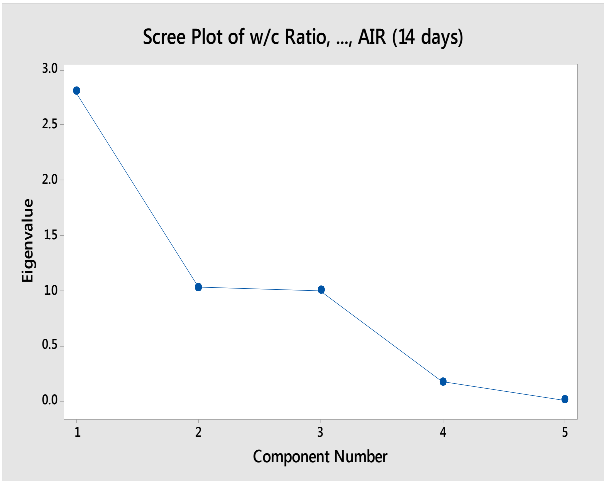

Fig. 5: Screen Plot of AC.

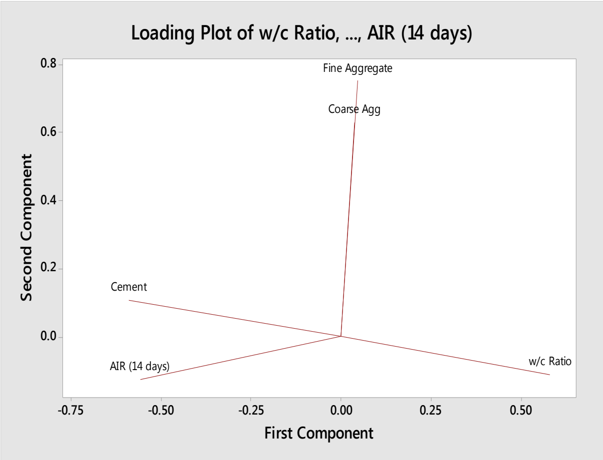

Fig. 6: Loading Plot of AC.

5.1.2. Water curing

Eigen vectors and their corresponding Eigen values were calculated and values are shown below Table 8 and Table 9 for WC. Fig. 7 explained PCs versus Eigen Values whereas the relation between First and Second PCs are shown in Fig. 8.

Table 8: Eigen Analysis of the Correlation Matrix (WC)

Eigen Value	2.7458	1.1402	1.0000	0.1070	0.0071
Proportion	0.549	0.228	0.200	0.021	0.001
Cumulative	0.549	0.777	0.977	0.999	1.000

Table 9: Eigen Vectors of the Correlation Matrix (WC)

Variable	PC1	PC2	PC3	PC4	PC5
w/c Ratio	0.576	-0.248	0.000	-0.384	0.678
Cement	-0.579	0.244	-0.000	0.265	0.731
CA	0.044	0.263	-0.956	-0.121	-0.009
FA	0.143	0.859	0.293	-0.394	-0.031
f_{ck} (14 days)	-0.557	-0.268	0.000	-0.783	-0.068

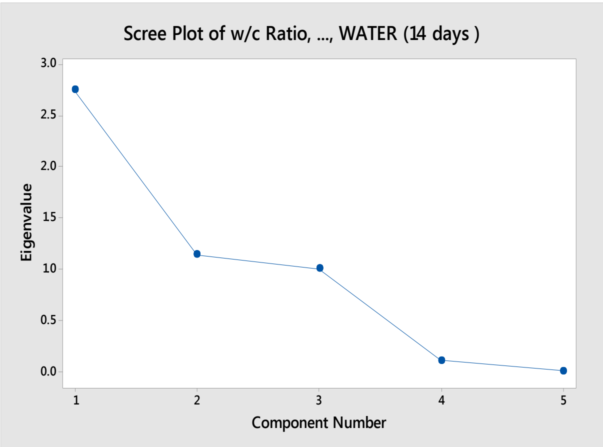

Fig. 7: Screen Plot of WC.

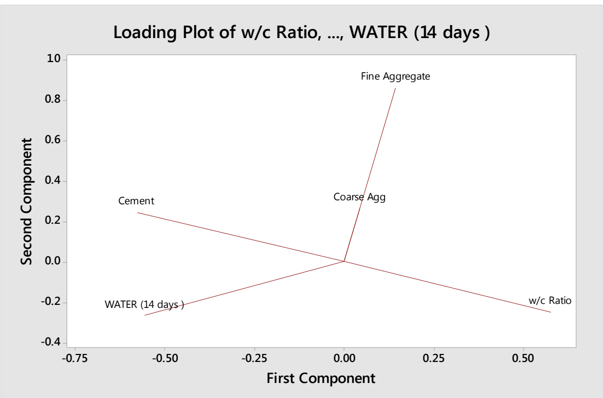

Fig. 8: Loading plot of WC.

5.1.3. Plastic bag curing

Eigen vectors and their corresponding Eigen values were calculated and values are shown below Table 10 and Table 11 for PBC respectively. Fig. 9 explained PCs versus Eigen Values whereas the relation between First and Second PCs are shown in Fig. 10 for PBC.

Table 10: Eigen Analysis of the Correlation Matrix (PBC)

Eigen Value	2.8660	1.0601	1.0000	0.0695	0.0045
proportion	0.573	0.212	0.200	0.014	0.001
Cumulative	0.573	0.785	0.985	0.999	1.000

Table 11: Eigenvectors of the Correlation Matrix (PBC)

Variable	PC1	PC2	PC3	PC4	PC5
w/c Ratio	0.575	-0.171	-0.000	0.521	-0.607
Cement	-0.580	0.166	0.000	-0.203	-0.771
CA	0.063	0.611	0.769	0.175	0.038
FA	0.076	0.734	-0.639	0.210	0.046
f_{ck} (14 days)	-0.568	-0.177	-0.000	0.783	0.183

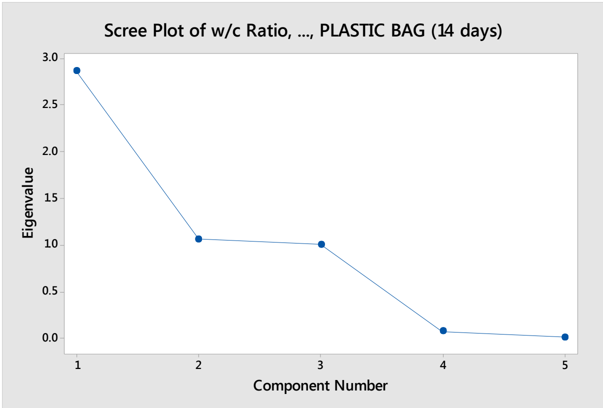

Fig. 9: Screen Plot of PBC.

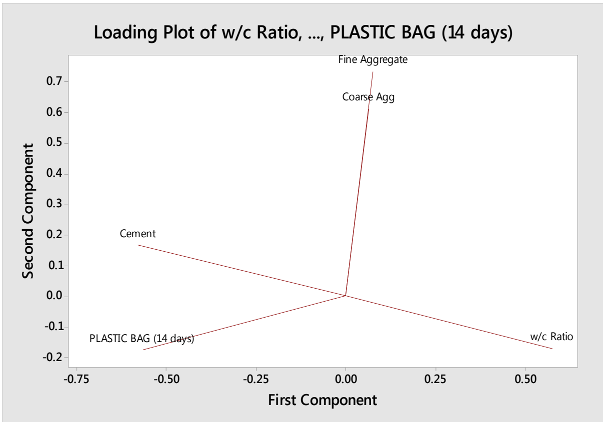

Fig. 10: Loading Plot of PBC.

The simulation runs was performed by MINITAB and MATLAB programmer and the results are summarized. From the Principal Component Analysis, it is observed a total of 97% variability of data set is explained by first three Principal components in case of AC whereas 98% in case of WC and 99% for PBC.

Ranks of ingredients of concrete mixes are obtained from first three PC Scores and also from loading graphs. Ranks show the influencing intensity of ingredients on CS of Concrete mixes.

It is also observed that from the analysis, w/c is the first most influencing variable whereas cement is the second most influencing variable of CS of concrete mixes for Air and PB curing. In case of Water Curing, CA and w/c are the first and second most influencing variables of CS of concrete mixes. FA is showing least influence on CS of concrete mixes.

6. Conclusions

The following Conclusions are made from the present investigations

1) Concrete mixes with 9 combinations for 3 levels were considered for the study.
2) Different parameters influencing the concrete mix namely water cement ratio, Cement, Coarse Aggregate and Fine Aggregate were considered for analysis.
3) PCA technique reduces experimental cost and time for selected optimum mix.
4) Water Cured samples showed higher Compressive Strength for all mixes when compared with all types of curing methods whereas Air Cured samples showed lower strengths.
5) At 0.36 water cement ratio, Compressive Strength of mixes are more when compared to the other water cement ratios at all curing conditions and curing period.
6) Compressive Strength of mixes for Water Cured Samples is 9 to 15% higher than Compressive Strength for Air Cured samples.
7) When compared to Air Curing, Compressive Strength for Plastic Bag Curing is 3.7 to 6.29% higher.
8) The contribution rate of first, second and third component of Principal Components for Air Curing, Water Curing and Plastic Bag Curing are 97 %, 98 % and 99 % respectively.
9) The first most influencing variable is w/c whereas cement is the second most influencing variable of Compressive Strength of concrete mixes for Air Curing and Plastic Bag Curing. In case of Water Curing, Coarse Aggregate and w/c are the first and second most influencing variables of Compressive Strength of concrete mixes. Fine Aggregate is showing least influence on Compressive Strength of concrete mixes.

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