Manipal Journal of Science and Technology

Volume 5 | Issue 1 Article 2

6-1-2020

POD in Concrete Performance Assessment

A Manoj
National Institute of Technology Karnataka, Surathkal, India., manoja1990@gmail.com

Research Article

POD in Concrete Performance Assessment

A Manoj*, K S Babu Narayan

Email: manoja1990@gmail.com

Abstract

The quality of ingredients and their quantity in the concrete mix decide the performance level. As the number of variables on which concrete performance depends increases, it is essential to identify those, to which the performance characteristics are sensitive. Efficacy of Proper Orthogonal Decomposition (POD) in the visualisation of patterns in data, its utility in the identification of crucial variables, prediction of performance levels, and generation of performance indices have been discussed and illustrated.

Keywords: Concrete, POD, Data, Correlation, Performance index.

Introduction

Mouldability to any conceivable shape has made concrete the most popular and versatile material of construction. Workability, strength, and durability are the cardinal properties of concrete, which are prescribed appropriately as per construction work requirements. Mix proportion, admixture dosage, method of mixing, handling and curing, exposure and loading conditions decide the performance throughout the utility period [1].

Quantification of the influence of variables on performance levels provides insights into ways of accomplishments of targeted performance levels. POD is a great tool in such exercises.

POD and Concrete

POD, a dimensionality reduction technique founded on Eigenvalue and Singular value decomposition [2], [3], formed as Principal Component Analysis [4], [5], developed [6]–[10], and has emerged as a powerful data handling tool in a variety of applications.

A Manoj[1], K S Babu Narayan[2]

[1] *Research Scholar, Department of Civil Engineering, National Institute of Technology Karnataka, Surathkal, 575025, India.*

[2] *Professor, Department of Civil Engineering, National Institute of Technology Karnataka, Surathkal, 575025, India.*

Manuscript received: 21 March 2020
Revision accepted: 12 April 2020

* Corresponding Author

POD has been extensively used individually or in combination with other techniques like Artificial Neural Network, Genetic Algorithm for assessment of historical monuments [11]–[14], and analysis of experimental data of concrete [15]–[18]. Availability of exhaustive data on concrete and advancements in computational facilities and techniques [19] have contributed to the enhancement of concrete performance prediction.

Methodology

Data on variables that influence performance is acquired, organised, and rationalised. Classification of variables to quantitative and qualitative sets and generation of derived variable sets are done from recognised, established relationships. Normalisation is done next to avoid bias.

The correlation matrix is generated and subjected to orthogonal decomposition. Eigenvalues (λ_i) and eigenvectors (v_i) obtained from decomposition, are of utility in determination of performance indicators and interpretation. Eigenvectors obtained are the linear combination of initial variables. Eigenvalues quantify the amount of variation and eigenvectors show the direction in which variation is seen in the data cloud being analysed. Eigenvalues indicate the degree to which variation is captured and the number of components to be counted for further analysis, is decided by their cumulative contribution in capturing total variation.

How to cite this article: A Manoj, K S Babu Narayan. “POD in Concrete Performance Assessment”, Manipal J. Sci. Tech., vol.5(1), 8-11, 2020.

Component plots are drawn to graphically represent analysis results. Based on significant correlation (which is generally considered to be more than |±0.7| [8]), and component plot analysis, critical variables are identified.

Illustrative example

Dataset for analysis

A part of available data "Innovative Cement Combinations for Concrete Performance" [20] has been chosen to demonstrate the utility of POD in evaluating the performance of concrete.

Ordinary Portland Cement–CEMI (PC, 225-475 kg/m^3), Fine aggregate (FA, 650-835 kg/m^3), 10 mm downsize coarse aggregate (CA5_10, 375-380 kg/m^3), 20 mm downsize coarse aggregate (CA10_20, 750-760 kg/m^3), water to cement ratio (0.35-0.65) and superplasticizer (SP, 0.15-0.41% of cement) to maintain S2 consistency (i.e., Nominal slump of 75±25 mm, [21]) are the available data on mix proportion. Across all mixes, 165 kg/m3 quantity of water has been maintained.

Cube compressive strengths at 3, 7, 28, 90, and 180 days (CS3, CS7, CS28, CS90, CS180), Initial Surface Absorption (ISAT28, ISAT180), Sorptivity (SRP28, SRP180), Water penetration (WP28, WP180) and Air permeability (AP28, AP180) at 28 and 180 days are also available as data on-target performances.

Results

Data has been screened, and the correlation matrix for normalised data is subject to orthogonal decomposition. Table I presents a list of the eigenvalues. Correlation values of mix proportion and target performance characteristics are presented in Table II.

Table I: Eigenvalues

λ_i	λ_1	λ_2	λ_3	λ_4	λ_5
Eigenvalue	16.78	1.46	0.62	0.11	0.03
% variation contribution	88.31	7.67	3.28	0.60	0.14
Cumulative % variation	88.31	95.98	99.26	99.86	100

Table II: Correlation values

	PC	FA	CA5_10	CA10_20	w/c	SP
CS3	0.99	-0.99	-0.93	-0.55	-0.97	0.84
CS7	0.99	-0.99	-0.92	-0.52	-0.98	0.84
CS28	0.99	-0.98	-0.92	-0.53	-0.98	0.83
CS90	0.99	-0.99	-0.91	-0.51	-0.98	0.83
CS180	0.99	-0.99	-0.92	-0.51	-0.99	0.82
ISAT28	-0.89	0.91	0.76	0.3	0.92	-0.88
ISAT180	-0.9	0.92	0.76	0.28	0.94	-0.9
SRP28	-0.95	0.97	0.8	0.29	0.99	-0.8
SRP180	-0.95	0.97	0.8	0.29	0.99	-0.8
WP28	-0.96	0.98	0.81	0.29	0.99	-0.71
WP180	-0.95	0.96	0.8	0.3	0.98	-0.76
AP28	-0.79	0.82	0.63	0.16	0.84	-0.9
AP180	-0.78	0.81	0.63	0.16	0.83	-0.93

Eigenvalues are represented in the form of a Pareto chart, as shown in Figure 1. Elbow at second

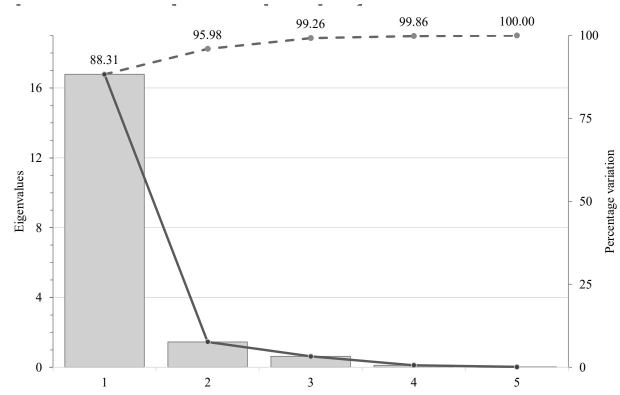

Fig 1: Pareto chart for the Eigenvalues

Correlation/component plots are generated by plotting two components against each other. For the first two components, the component plot is as presented in Figure 2.

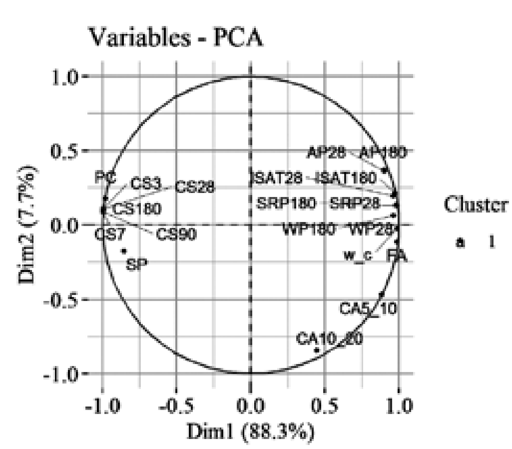

Fig 2: Component plot

A Manoj *et al*: POD in Concrete Performance Assessment

From Table II and Figure 2, it is evident that compressive strength at all ages has a strong and positive correlation with cement content and superplasticiser dosage, whereas it has a strong negative correlation with water-cement ratio and fine aggregate content.

Increased water-cement ratio and fine aggregate contents increase surface adsorption, sorption, water, and air permeation characteristics.

As the correlation of 20 mm downsize coarse aggregate content is weak with all the performance characteristics (which is less than |±0.7|) and as it lies farther to any variable in the component plot, it can be inferred that it has very little role in influencing targeted performance.

Performance index

An index has been developed to assess the performance of concrete as detailed in eq. 1.

$$PI_x = \left(\frac{1}{n}\sum_{k=1}^{n} C_{1,v_k}\frac{v_k}{v_{k,ref}}\right)\times C_{1,x} + \left(\frac{1}{n}\sum_{k=1}^{n} C_{2,v_j}\frac{v_k}{v_{k,ref}}\right)\times C_{2,x} \quad \ldots(\text{eq. } 1)$$

Here, PI = Performance index value, n = Number of important variables, c = Coefficient of variables in component, v_k = Quantity of variable and $v_{k,ref}$ = Reference value, which is considered to be a maximum value of a variable.

Positively and negatively correlated variables among identified crucial variables are grouped separately and indices are computed. Thus, arrived indices are used in performance appraisal.

All variables with significant correlation have been considered for the computation of the performance index. Computed values of performance indices are presented in Table III. Sign of index speaks of nature of effect and magnitude quantifies the effect. These indices give an idea of the relative performance of concrete mixes.

For instance, consider the cases of C135A and CS135B compressive strength at three days (CS3) for performance valuation. These mixes have the same water-cement ratios of 0.35, same mix proportion except the dosage of the superplasticiser. The index values are (0.91,-0.74) and (0.84,-0.74) for C135A and C135B mixes respectively. Though negative values are the same, the positive value is more for C135A, and hence CS3 must be higher for C135A as per PI. The reported values of CS3 for C135A and C135B being 53 MPa and 49.5 MPa respectively, are consistent with the inference from the results of POD.

Conclusions

POD is a powerful method of data handling, and its efficacy has been demonstrated in the performance appraisal of concrete mixes. The performance indices of the sort developed immensely help in discrimination, selection, and adoption of the most appropriate mix for works. Implications of additions,

Table III: Index Values

MIX ID	C135A		C150A		C165A		C135B		C150B		C165B	
Performance Characteristic, x	+	-	+	-	+	-	+	-	+	-	+	-
CS3	0.91	-0.74	0.71	-0.86	0.53	-0.97	0.84	-0.74	0.55	-0.86	0.42	-0.97
CS7	0.91	-0.73	0.71	-0.86	0.53	-0.96	0.84	-0.73	0.55	-0.86	0.42	-0.96
CS28	0.91	-0.73	0.71	-0.86	0.53	-0.96	0.84	-0.73	0.54	-0.86	0.42	-0.96
CS90	0.91	-0.73	0.71	-0.86	0.53	-0.96	0.84	-0.73	0.55	-0.86	0.42	-0.96
CS180	0.91	-0.73	0.71	-0.86	0.53	-0.96	0.84	-0.73	0.55	-0.86	0.42	-0.96
ISAT28	0.66	-0.88	0.77	-0.69	0.87	-0.51	0.66	-0.81	0.77	-0.52	0.87	-0.40
ISAT180	0.66	-0.89	0.78	-0.70	0.88	-0.52	0.66	-0.82	0.78	-0.53	0.88	-0.40
SRP28	0.68	-0.90	0.80	-0.70	0.90	-0.52	0.68	-0.83	0.80	-0.54	0.90	-0.41
SRP180	0.68	-0.90	0.81	-0.70	0.91	-0.53	0.68	-0.83	0.81	-0.54	0.91	-0.41
WP28	0.68	-0.88	0.80	-0.69	0.90	-0.51	0.68	-0.81	0.80	-0.53	0.90	-0.40
WP180	0.68	-0.88	0.80	-0.69	0.90	-0.51	0.68	-0.81	0.80	-0.52	0.90	-0.40
AP28	0.58	-0.82	0.69	-0.65	0.78	-0.48	0.58	-0.75	0.69	-0.49	0.78	-0.37
AP180	0.58	-0.82	0.69	-0.65	0.78	-0.48	0.58	-0.75	0.69	-0.48	0.78	-0.37

deletions, and substitution of ingredients can also be assessed.

References

[1] Y. Pan, A. Prado, R. Porras, O. M. Hafez, and J. E. Bolander, "Lattice modeling of early-age behavior of structural concrete," Materials (Basel)., vol. 10, no. 3, pp. 1–34, 2017.

[2] E. Beltrami, "Sulle funzioni bilineari," G. di Mat. ad Uso degli Studenti Delle Univ., vol. 11, no. 2, pp. 98–106, 1873.

[3] C. Jordan, "Mémoire sur les formes bilinéaires," J. Math. Pures Appl., vol. 19, pp. 35–54, 1874.

[4] K. Pearson, "On lines and planes of closest fit to systems of points in space," London, Edinburgh, Dublin Philos. Mag. J. Sci., vol. 2, no. 11, pp. 559–572, 1901.

[5] H. Hotelling, "Analysis of a complex of statistical variables into principal components," J. Educ. Psychol., vol. 24, no. 6, pp. 417–441, 1933.

[6] T. W. Anderson, "Asymptotic theory for principal component analysis," Ann. Math. Stat., vol. 34, no. 1, pp. 122–148, 1963.

[7] J. C. Gower, "Some distance properties of latent root and vector methods used in multivariate analysis," Biometrika, vol. 53, no. 3–4, pp. 325–338, 1966.

[8] J. N. R. Jeffers, "Two case studies in the application of principal component analysis," J. R. Stat. Soc. Ser. C (Applied Stat.), vol. 16, no. 3, pp. 225–236, 1967.

[9] I. T. Jolliffe, Principal Component Analysis, Second Edi. New York: Springer, 2002.

[10] Y. C. Liang, H. P. Lee, S. P. Lim, W. Z. Lin, K. H. Lee, and C. G. Wu, "Proper Orthogonal Decomposition and Its Applications—Part I: Theory," J. Sound Vib., vol. 252, no. 3, pp. 527–544, May 2002.

[11] A. Moropoulou, K. Polikreti, A. Bakolas, and P. Michailidis, "Correlation of physicochemical and mechanical properties of historical mortars and classification by multivariate statistics," Cem. Concr. Res., vol. 33, pp. 891–898, 2003.

[12] L. Rampazzi, A. Pozzi, A. Sansonetti, L. Toniolo, and B. Giussani, "A chemometric approach to the characterisation of historical mortars," Cem. Concr. Res., vol. 36, no. 6, pp. 1108–1114, 2006.

[13] A. Hellebois, A. Launoy, C. Pierre, M. De Lanève, and B. Espion, "100-year-old Hennebique concrete, from composition to performance," Constr. Build. Mater., vol. 44, pp. 149–160, 2013.

[14] E. Arizio, R. Piazza, W. R. L. Cairns, L. Appolonia, and A. Botteon, "Statistical analysis on ancient mortars : A case study of the Balivi Tower in Aosta (Italy)," Constr. Build. Mater., vol. 47, pp. 1309–1316, 2013.

[15] B. Boukhatem, M. Ghrici, S. Kenai, and A. Tagnit-hamou, "Prediction of Efficiency Factor of Ground-Granulated Blast," ACI Mater. J., no. 108, pp. 1–10, 2011.

[16] B. Boukhatem, S. Kenai, A. T. Hamou, D. Ziou, and M. Ghrici, "Predicting concrete properties using Neural Networks (NN) with Principal Component Analysis (PCA) technique," Computers and Concrete, vol. 10, no. 6. pp. 557–573, 2012.

[17] S. C. Yaragal, B. C. Kumar, and K. Mate, "Optimization of ferrochrome slag as coarse aggregate in concretes," Comput. Concr., vol. 23(6), no. July, pp. 421–431, 2019.

[18] A. Manoj and K. S. B. Narayan, "Application of Proper Orthogonal Decomposition in Concrete Performance Appraisal," in Recent Trends in Civil Engineering, Springer, 2021, pp. 13–21.

[19] B. Boukhatem, S. Kenai, A. Tagnit-Hamou, and M. Ghrici, "Application of new information technology on Concrete: An Overview," J. Civ. Eng. Manag., vol. 17, no. 2, pp. 248–258, Jul. 2011.

[20] R. K. Dhir, M. D. Newlands, M. J. McCarthy, L. Zheng, and J. E. Halliday, "Innovative Cement Combinations for Concrete Performance–Final Report CTU/5009," 2010.

[21] British Standards Institution, BS EN 206-1:2000 Concrete. Specification, performance, production and conformity. London, 2000.