**Computers and Concrete**, *Vol. 23, No. 6 (2019) 421-431*
DOI: https://doi.org/10.12989/cac.2019.23.6.421


# Optimization of ferrochrome slag as coarse aggregate in concretes

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*(Received January 31, 2019, Revised April 20, 2019, Accepted April 23, 2019)*

**Abstract.** The alarming rate of depletion of natural stone based coarse aggregates is a cause of great concern. The coarse aggregates occupy nearly 60-70% by volume of concrete being produced. Research efforts are on to look for alternatives to stone based coarse aggregates from sustainability point of view. Response surface methodology (RSM) is adopted to study and address the effect of ferrochrome slag (FCS) replacement to coarse aggregate replacement in the ordinary Portland cement (OPC) based concretes. RSM involves three different factors (ground granulated blast furnace slag (GGBS) as binder, flyash (FA) as binder, and FCS as coarse aggregate), with three different levels (GGBS (0, 15, and 30%), FA (0, 15, and 30%) and FCS (0, 50, and 100%)). Experiments were carried out to measure the responses like, workability, density, and compressive strength of FCS based concretes. In order to optimize FCS replacement in the OPC based concretes, three different traditional optimization techniques were used (grey relational analysis (GRA), technique for order of preference by similarity (TOPSIS), and desirability function approach (DFA)). Traditional optimization techniques were accompanied with principal component analysis (PCA) to calculate the weightage of responses measured to arrive at the final ranking of replacement levels of GGBS, FA, and FCS in OPC based concretes. Hybrid combination of PCA-TOPSIS technique is found to be significant when compared to other techniques used. 30% GGBS and 50% FCS replacement in OPC based concrete was arrived at, to be optimal.

**Keywords:** coarse aggregate; ferrochrome slag; grey relational analysis; technique for order of preference by similarity; desirability function approach

## 1. Introduction

Due to the rapid increase in infrastructure development, depletion of natural resources in the construction industries has posed a serious challenge to researchers (Katpady *et al.* 2015, Karanth *et al.* 2017). To address this issue, one is now forced to look for alternatives as replacement to natural stone aggregates (Prusty *et al.* 2015, Sunil *et al.* 2015, Mukharjee and Barai 2015, Yaragal *et al.* 2016, Yaragal and Roshan 2017, Dan *et al.* 2018). Keeping this motto in mind, several researchers are working in the area of sustainable concrete production. Production of concrete requires large volume of natural coarse aggregate (NCA). Over exploitation of NCA is a serious threat for future generation in the concrete production too. One remedial measure to reduce the use of NCA is by use of industrial byproducts optimally. Further, utilization of industrial byproducts in the concrete production will also reduce the associated landfill problems.

Ferrochrome slag (FCS) is an industrial byproduct of Ferro-alloy industries. Stainless steel industry requires ferrochrome alloy for production of stainless steel. Lind *et al.* (2001) have carried out experiments on the utilization of FCS in road construction. Nath (2018) used FCS as binder to study the geopolymerization behaviour of FCS and FA blends. Dash and Patro (2018a, b) studied the effect of FCS as fine aggregate in concrete. Acharya and Patro (2016) reported the use of FCS in lieu with NCA. Zelic (2005) and Gencel *et al.* (2012) used FCS as NCA and identified that FCS replacement has a significant influence on compressive strength. Gencel *et al.* (2012) utilized FCS as coarse aggregate instead of limestone aggregate with three replacement levels of 25, 50, and 75%. FCS as coarse aggregate influences the hardened properties of concrete such as strength, and wear resistance. Al-jabri *et al.* (2018) have used image analysis to find roughness index of FCS and natural fine aggregate. Roughness index was found to be around 142.48 and 36 microns for FCS and natural fine aggregate respectively. To get required workability, additional water was essential for the use of FCS as replacement to natural fine aggregate. Requirement of additional water was due to higher surface area and rough surface texture of FCS. Mechanical properties of FCS replaced mixes were also improved due to the phenomena of “Mechanical Interlacing” of aggregate and paste system in the interfacial transition zone (ITZ) region.

### *1.1 Design of experiments and multi objective optimization*

Acharya and Patro (2016) carried out full factorial analysis by considering single factor and single response at a time. Singh *et al.* (2016) involved design of experiments to reduce the number of experiments since full factorial

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ISSN: 1598-8198 (Print), 1598-818X (Online)

Table 1 Physical properties of OPC, GGBS, and FA

| Constituents | Specific gravity | Fineness | Color | LOI (%wt) |
|---|---|---|---|---|
| OPC | 3.14 | 340 | Grey | 1.4 |
| GGBS | 2.9 | 370 | White | 1.2 |
| FA | 2.22 | 205 | Light Grey | 0.4 |

Note: LOI = Loss of ignition

Table 2 Chemical composition of OPC, GGBS, FA, and FCS (% weight)

| Constituents | CaO | $Al_2O_3$ | $Fe_2O_3$ | $SiO_2$ | MgO | $Na_2O$ | $K_2O$ | $SO_3$ | $Cr_2O_3$ | MnO |
|---|---|---|---|---|---|---|---|---|---|---|
| OPC | 59.53 | 9.12 | 3.52 | 20.34 | 2.02 | 0.19 | 0.42 | 2.39 | - | - |
| GGBS | 36.72 | 17.14 | 1.30 | 34.45 | 4.50 | 0.14 | 0.06 | 0.88 | - | - |
| FA | 0.80 | 32.08 | 2.93 | 58.91 | 0.94 | 0.36 | 1.12 | 0.49 | - | - |
| FCS (Present study) | 8.99 | 18.15 | - | 28.08 | 23.19 | - | - | - | 19.88 | 1.70 |
| FCS (Acharya and Patro 2016) | 9.06 | 24.70 | 3.81 | 27.50 | 22.50 | 0.40 | | - | 9.34 | - |
| FCS (Nath 2018) | 12.55 | 26.05 | 2.20 | 22.70 | 25.30 | - | - | - | 4.15 | - |

analysis is time consuming and uneconomical, and also grey relational analysis (GRA) were adopted as multi objective optimization method to obtain optimal mixture. Simsek *et al.* (2013) proposed a technique for order of preference by similarity (TOPSIS) as multi objective optimization method to obtain optimal mixture. Sengul and Tasdemir (2009) adopted desirability function approach (DFA) to find optimal mixture. All the three methods were carried out for equal weightage of responses. Majumder *et al.* (2017) showed the importance of principal component analysis (PCA) in weightage calculation of each multi objective optimization methods stated above. Further, Sadhukhan *et al.* (2014) showed that different multi objective optimization methods yields different optimal values and suggested spearmen's correlational coefficient method.

### *1.2 Objective and research significance*

Although several studies are available, there is still scope for optimization of FCS utilization under multi objective condition with industrial byproducts as binder in concrete. Optimization of concrete mixtures usually involves several responses simultaneously, such as high workability, low density, and high compressive strength under fresh and hardened states. High workability is good for placement of concrete in the fresh state. Low density of concrete reduces the dead weight of concrete. Reduced dead weight can reduce the stresses, total quantity of steel required, and cost of reinforced concrete structure (RCC). Also, high compressive strength of concrete is important from the structural safety point of view. In order to obtain high workability, low density, and high compressive strength concrete mixtures, multi objective optimization methods (GRA, TOPSIS, and DFA) are preferred, in which the slump and compressive strength is to be maximized but the density of concrete is to be minimized. Weightage for each responses in multi objective optimization method were calculated based on the PCA. In the present study, multi objective optimization methods were coupled with Spearman's correlation coefficients calculation. Spearman's correlation coefficients are invoked in between different multi objective optimization methods, since different multi objective optimization methods are likely to yield different optimal results.

This paper is an effort towards sustainable construction by way of reducing the amount of conventional binder and NCA in concretes. Industrial byproducts such as GGBS, FA, and FCS were utilized as binder and aggregate, instead of discarding them into landfills. Also, multi objective optimization method provides suitable optimal mixtures for the decision maker under different set of responses.

## 2. Materials and methodology

### *2.1 Materials*

#### *2.1.1 Binder*

Ordinary Portland cement (OPC) of 53 grade (IS-12269:2013) is used as primary binder in the preparation of concrete. Physical and chemical properties of OPC are presented in Tables 1-2 respectively. The compressive strength of cement using standard Ennore sand were measured to be around 46.4 MPa, and 57.5 MPa for 7, and 28 days respectively. GGBS and FA are used as supplementary cementitious materials (binder) in the preparation of FCS based concretes. Physical and chemical properties of GGBS (IS-12089:1987) and FA (IS-3812(P1):2013) are also presented in Tables 1-2 respectively. GGBS is procured from M/s JSW, Iron and steels limited, Bellary, India. FA is procured from M/s Adani Power Ltd. (Udupi thermal power plant, Ltd.,) Udupi, India. FA used belongs to class F grade.

#### *2.1.2 Fine aggregate*

Natural river sand is used as fine aggregate. Fine aggregate was sourced from Gurupura River, Dakshina Kannada, India. Fine aggregate confirms to zone II requirement of IS-383:2016. Specific gravity, water absorption, compacted dry bulk density, and fineness modulus of fine aggregate were 2.54, 0.9%, 1681 kg/m$^3$ and 2.59 respectively. Fine aggregate used was free from deleterious materials and in surface saturated dry condition for producing concrete. Table 3 presents the results of sieve analysis.

#### *2.1.3 Coarse aggregate*

NCA was procured from local market and FCS was supplied by M/s Balasore alloys limited, Balasore, Odissa, India. NCA and FCS were used as coarse aggregate in the

Table 3 Sieve analysis results of fine aggregate

| Sieve size | 10 mm | 4.75 mm | 2.36 mm | 1.18 mm | 600$\mu$ | 300$\mu$ | 150$\mu$ |
|---|---|---|---|---|---|---|---|
| Cumulative percentage passing | 100 | 98 | 96.2 | 75.3 | 53.6 | 14.8 | 2.9 |
| Remarks | Zone II (As per IS-383:2016) | | | | | | |

Table 4 Sieve analysis results of NCA and FCS

| Sieve size | 25 mm | 20 mm | 10 mm | 4.75 mm |
|---|---|---|---|---|
| Cumulative percentage passing NCA | 100 | 100 | 44 | 2 |
| Cumulative percentage passing FCS | 100 | 100 | 47 | 3 |
| Remarks | NCA and FCS used satisfies the requirements of IS-383:2016 | | | |

preparation of concretes. NCA and FCS both confirm to the requirement of IS-383:2016. Sieve analysis results for both NCA and FCS are given in Table 4. Specific gravity, water absorption, and compacted dry bulk density of NCA were 2.62, 0.4%, and 1723 kg/m$^3$ respectively. Similarly, specific gravity, water absorption, and compacted dry bulk density of FCS were 3.14, 0.8%, and 2182 kg/m$^3$ respectively. Further, various test results of NCA like aggregate crushing value, Los Angeles abrasion value, aggregate impact value, flakiness index, and elongation index (IS-2386:1963 reaffirmed in 2002) were conducted with experimental results of 30.4, 30.6, 20.6, 12, and 24% respectively. Similarly, for FCS these results were 20, 25, 16, 13, and 25% respectively. Both NCA and FCS satisfies the codal requirement to be used as coarse aggregate.

#### *2.1.4 Water*

Potable tap water that confirming to IS-456:2000 is used for mixing and curing of the concrete mixes.

#### *2.1.5 Super-plasticizer*

A commercially available CONPLAST SP 430 (FOSROC make), Sulfonated Naphthalene Formaldehyde (SNF)-polymer based high-range water-reducing admixture is used as a super plasticizer (SP) in the present investigation. Specific gravity being around 1.18 at 25$^0$C. SP used confirms to IS-9103:1999.

### *2.2 Testing of concrete*

In order to obtain required workability of concrete, with different industrial byproduct replacement slump tests were performed on fresh concrete. Density of concrete mixtures were calculated using the sum of all the ingredients used in the concrete mixture preparation. Compressive strengths of concretes were determined as per IS-516:1959. Compressive strength test on cast specimen were conducted at 28 and 90 days interval, to optimize GGBS, FA, and FCS replacement levels in OPC based concretes.

### *2.3 Design of experiments*

Replacement of industrial byproducts in concrete is a multi-variable process, in which different factors (like industrial byproducts as binder and coarse aggregate) can affect the process of workability, density and mechanical strength of concrete. Design of experiments was employed using response surface methodology (RSM). RSM through Box-Behnkan design (BBD) was adopted to study the effect of GGBS, FA, and FCS replacement in concretes. Three factors with three levels were identified and considered to

Table 5 Different factors and levels (Coded and Un-coded) used in Box-Behnkan design

| Factor | Levels | | |
|---|---|---|---|
| | 1 | 2 | 3 |
| GGBS (% wt) | 0 | 15 | 30 |
| FA (% wt) | 0 | 15 | 30 |
| FCS (% vol) | 0 | 50 | 100 |

Table 6 Experimental design for optimization of various influencing variables on concrete

| Run No | GGBS (% wt) | FA (% wt) | FCS (% vol) |
|---|---|---|---|
| 1 | 0 | 0 | 50 |
| 2 | 30 | 0 | 50 |
| 3 | 0 | 30 | 50 |
| 4 | 30 | 30 | 50 |
| 5 | 0 | 15 | 0 |
| 6 | 30 | 15 | 0 |
| 7 | 0 | 15 | 100 |
| 8 | 30 | 15 | 100 |
| 9 | 15 | 0 | 0 |
| 10 | 15 | 30 | 0 |
| 11 | 15 | 0 | 100 |
| 12 | 15 | 30 | 100 |
| 13 | 15 | 15 | 50 |
| 14 | 15 | 15 | 50 |
| 15 | 15 | 15 | 50 |

optimize the industrial byproducts replacement level in concrete. Table 5 shows different factors and different levels used in the present study. Table 6 gives component variables of different factors and their levels based on RSM-BBD for different concrete mixtures. Total fifteen concrete mixtures were prepared with 3 center points to represent full factorial experiments. Concrete mixtures were prepared according to IS-10262:2009 bureau of Indian standard for "Concrete mix proportioning – guidelines". Medium degree of workability i.e., slump range of 50-100mm was targeted in the present study, which can be used for RCC sections like slabs, beams, columns etc. Table 7 gives mixture proportion of fifteen experimental runs (three central points) with different materials used in the present study. Effect of GGBS, FA, and FCS in concretes were measured using responses like workability, density, and compressive strength.

### *2.4 Optimization techniques*

In the present study, different multi objective optimization techniques like GRA, TOPSIS, and DFA were employed. Different optimization techniques were used to check the effectiveness of different factors like GGBS, FA, and FCS content that have influence on the responses of concrete and also to convert multi response optimization problem (Slump, density, 28 days, and 90 days compressive strength) into single response optimization problem.

#### *2.4.1 Grey relational analysis (GRA)*

GRA is firstly introduced and formulated by Dang

Table 7 Concrete mixture proportion with different ingredients.

| Run No | OPC ($kg/m^3$) | GGBS ($kg/m^3$) | FA ($kg/m^3$) | Water ($kg/m^3$) | SP ($kg/m^3$) | NCA ($kg/m^3$) | FCS ($kg/m^3$) | Fine aggregate ($kg/m^3$) |
|---|---|---|---|---|---|---|---|---|
| 1 | 440 | 0 | 0 | 176 | 3 | 536 | 642 | 693 |
| 2 | 308 | 132 | 0 | 176 | 3 | 533 | 639 | 689 |
| 3 | 308 | 0 | 132 | 176 | 3 | 522 | 626 | 675 |
| 4 | 176 | 132 | 132 | 176 | 3 | 519 | 622 | 671 |
| 5 | 374 | 0 | 66 | 176 | 3 | 1058 | 0 | 684 |
| 6 | 242 | 132 | 66 | 176 | 3 | 1052 | 0 | 680 |
| 7 | 374 | 0 | 66 | 176 | 3 | 0 | 1268 | 684 |
| 8 | 242 | 132 | 66 | 176 | 3 | 0 | 1261 | 680 |
| 9 | 374 | 66 | 0 | 176 | 3 | 1069 | 0 | 691 |
| 10 | 242 | 66 | 132 | 176 | 3 | 1041 | 0 | 673 |
| 11 | 374 | 66 | 0 | 176 | 3 | 0 | 1281 | 691 |
| 12 | 242 | 66 | 132 | 176 | 3 | 0 | 1248 | 673 |
| 13 | 308 | 66 | 66 | 176 | 3 | 527 | 632 | 682 |
| 14 | 308 | 66 | 66 | 176 | 3 | 527 | 632 | 682 |
| 15 | 308 | 66 | 66 | 176 | 3 | 527 | 632 | 682 |

Julong. GRA is suitable for solving complicated interrelationships between multi factors and variables. GRA involves the following steps (Gopal and Prakash 2018, Singh *et al*. 2016).

Step 1: Normalization of responses

Normalization of responses usually involves whether the response to be maximized or minimized. In the present study, maximization and minimization of responses can be done using the Eqs. (1)-(2) respectively.

$$y^{*}_{i(k)} = \frac{(x_i^0 - \min x_i^0)}{(\max x_i^0 - \min x_i^0)} \quad (1)$$

$$y^{*}_{i(k)} = \frac{(\max x_i^0 - x_i^0)}{(\max x_i^0 - \min x_i^0)} \quad (2)$$

Where, $x_i^0$ = Responses value $\max x_i^0$ and $\min x_i^0$ = Maximum and minimum values of responses respectively

Step 2: Calculation of grey relational coefficient (GRC)

Eq. (3) is employed to calculate the GRC of normalized values from step 1.

$$\xi_{i(k)} = \frac{\Delta_{min} + \zeta\Delta_{max}}{\Delta_{oi(k)} + \zeta\Delta_{max}} \quad (3)$$

Where, $\Delta_{oi(k)}$ = Offset in the absolute values

$\Delta_{max}$ and $\Delta_{min}$ =Maximum and minimum values of $\Delta_{oi(k)}$

$\zeta$ =Characteristic coefficient

Step 3: Calculation of grey relational grade (GRG)

GRG can be computed using the Eq. (4)

$$\gamma_i = \frac{1}{n}\sum_{k=1}^{n} \omega\xi_{i(k)} \quad (4)$$

Where, n = Number of experimental runs

$\omega$= Weightage of each response

$\gamma_i$= Grey relational grade

*2.4.2 Technique for order of preference by similarity to ideal solution (TOPSIS)*

TOPSIS is one of the multi-objective based optimization technique. TOPSIS was mainly based on the closeness coefficient values. Closeness coefficient values involve the conversion of multi-objective responses into single dimensionless quantity. Following steps are involved in the calculation of closeness coefficient value (Vijayaraghavan *et al.* 2017, Mousavi-Nasab and Sotoudeh-Anvari 2017, Simsek *et al*. 2013).

Step 1: Preliminary step is to arrange the responses into matrix form

$$D_m = \begin{pmatrix} x_{11} & \cdots & x_{1n} \\ \cdots & \cdots & \cdots \\ x_{m1} & \cdots & x_{mn} \end{pmatrix}$$

Where, $x_{mn}$=Response of $i^{th}$ alternative about the $j^{th}$ attribute.

Step 2: Normalization of responses

Normalization of responses were done using the Eq. (5).

$$\gamma_{ij} = \frac{x_{ij}}{\sqrt{\sum_{i=1}^{n} x_{ij}^2}} \quad (5)$$

Where, $x_{ij}$= Actual values of responses

$\gamma_{ij}$= Normalized values of responses

Step 3: Calculation of weighted normalized responses

Weighted normalized responses were calculated using Eq. (6).

$$V_{ij} = \gamma_{ij} \times w_{ij} \quad (6)$$

Where, $w_{ij}$= Weight of response

$V_{ij}$ = Weighted normalized response

Step 4: Calculation of positive and negative ideal solution

Positive and negative ideal solution were calculated based on Eqs. (7a)-(7b).

$$V^{+}=\left\{(\sum_{i}^{max}U_{ij}\left|j\in J),(\sum_{i}^{min}\right|j\in J\left|i=1,2,3..m)\right.\right\} \\ =\left\{V_1^{+},V_2^{+},V_3^{+},.....V_n^{+}\right\} \tag{7a}$$

$$V^{-}=\left\{(\sum_{i}^{min}U_{ij}\left|j\in J),(\sum_{i}^{max}\right|j\in J\left|i=1,2,3..m)\right.\right\} \\ =\left\{V_1^{-},V_2^{-},V_3^{-},.....V_n^{-}\right\} \tag{7b}$$

Step 5: Calculation of Euclidean distance and closeness coefficient

Euclidean distance or separation were calculated using the positive and negative ideal solution using Eqs. (8a)-(8b). Closeness coefficient is evaluated based on Eq. (9).

$$D_i^{+}=\sqrt{\sum_{j=1}^{n}(V_{ij}-V_j^{+})^2},i=1,2,....i \tag{8a}$$

$$D_i^{-}=\sqrt{\sum_{j=1}^{n}(V_{ij}-V_j^{-})^2},i=1,2,....i \tag{8b}$$

$$CC=\frac{D^{-}}{D^{+}+D^{-}} \tag{9}$$

#### *2.4.3 Desirability function approach (DFA)*

To maximize (workability, and compressive strength) and minimize (density) the responses from DFA are used. DFA involves the following steps (Sengul and Tasdemir 2009).

Step 1: Conversion of responses into individual desirability ($d_i$)

Individual desirability is computed based on whether the responses are to be maximized or minimized. In the present case, slump value and compressive strengths at 28 and 90 days are to be maximized and density to be minimized. To maximize or minimize responses, each response is to be translated into individual desirability. Eqs. (10)-(11) are used to maximize and minimize the responses into individual desirability respectively. Individual desirability will vary between 0-1.

$$d_i=\begin{cases}0 & y_i\le y_{imin}\\ \left[\dfrac{y_i-y_{i\,min}}{y_{i\,max}-y_{i\,min}}\right]^r & y_{imin}<y_i<y_{imax}\\ 1 & y_i\ge y_{imax}\end{cases} \tag{10}$$

$$d_i=\begin{cases}0 & y_i\le y_{imin}\\ \left[\dfrac{y_{i\,max}-y_i}{y_{i\,max}-y_{i\,min}}\right]^r & y_{imin}<y_i<y_{imax}\\ 1 & y_i\ge y_{imax}\end{cases} \tag{11}$$

Where, $y_i$ = Individual responses value

$y_{imax}$ and $y_{imin}$ = Maximum and minimum values of responses

$d_i$ = Individual desirability value

$r$= Weight to determine the scale of individual desirability

Step 2: Calculation of overall desirability (D)

Each individual desirability values were converted to overall desirability. Overall desirability can be computed using the Eq. (12). Higher value of overall desirability, indicates that it is preferable mixture. The lower value of overall desirability indicates the worst case, and the higher value of overall desirability was considered as optimum.

$$D=(d_1\times d_2\times....d_n)^{\frac{1}{n}} \tag{12}$$

Where, $D$ = Overall desirability of responses value

$d_1$, $d_2$, $d_3$…. $d_n$ = Individual desirability ($d_i$) and n represents a number of experimental runs.

### *2.5 Principal component analysis (PCA) for weights calculation for responses*

PCA or dimensionality reduction technique, is first introduced by Pearson in 1901, further developed by Hotelling in 1933. PCA is a multivariate statistical analysis technique which explains the construction of variance and co-variance of all the performance characteristics by linearly integrating them. The different steps involved in PCA are detailed as follows (Kaushik and Singhal 2018, Majumder *et al.* 2017).

Step 1: It starts with developing original multiple quality characteristic array.

$$X=\begin{pmatrix}x_1(1) & x_1(2) & ... & x_1(n)\\ x_2(1) & x_2(2) & ... & x_2(n)\\ ... & ... & ... & ...\\ x_m(1) & x_m(2) & ... & x_m(n)\end{pmatrix}$$

Where, $m$ is the number of experiments, $n$ is the number of responses and $x$ is the normalized values of responses. In the present paper $m$= 15, $n$= 4.

Step 2: Computation of correlation coefficient

Correlational coefficient array is developed using Eq. (13).

$$R_{jl}=\left(\frac{Cov(x_i(j),x_i(l))}{\sigma x_i(j)\times\sigma x_i(l)}\right) \tag{13}$$

Where, $Cov(x_i(j),x_i(l))$ is the covariance of sequences $x_i(j)$ and $x_i(l)$, $\sigma x_i(j)$ is the standard deviation of sequence $x_i(j)$, and $\sigma x_i(l)$ is the standard deviation of sequence $x_i(l)$.

Step 3: Computation of Eigen values and Eigen vectors.

The Eigen vectors and Eigen values are computed from the correlation coefficient array using Eq. (14).

$$(R-\lambda_k I_m)V_{ik}=0 \tag{14}$$

Table 8 Box-Behnkan design (BBD) and results

| Run No | Test design | | | Test results | | | |
|---|---|---|---|---|---|---|---|
| | GGBS (% wt) | FA (% wt) | FCS (% vol) | Slump (mm) | Density (kg/m$^3$) | Compressive strength at 28 days (MPa) | Compressive strength at 90 days (MPa) |
| 1 | 0 | 0 | 50 | 59 | 2490 | 61 | 63 |
| 2 | 30 | 0 | 50 | 66 | 2480 | 63 | 69 |
| 3 | 0 | 30 | 50 | 71 | 2442 | 50 | 61 |
| 4 | 30 | 30 | 50 | 72 | 2431 | 39 | 44 |
| 5 | 0 | 15 | 0 | 77 | 2361 | 54 | 55 |
| 6 | 30 | 15 | 0 | 61 | 2351 | 49 | 51 |
| 7 | 0 | 15 | 100 | 67 | 2571 | 54 | 55 |
| 8 | 30 | 15 | 100 | 58 | 2560 | 49 | 51 |
| 9 | 15 | 0 | 0 | 61 | 2379 | 60 | 66 |
| 10 | 15 | 30 | 0 | 71 | 2333 | 50 | 52 |
| 11 | 15 | 0 | 100 | 63 | 2591 | 60 | 64 |
| 12 | 15 | 30 | 100 | 66 | 2540 | 48 | 53 |
| 13 | 15 | 15 | 50 | 64 | 2460 | 53 | 56 |
| 14 | 15 | 15 | 50 | 64 | 2460 | 53 | 56 |
| 15 | 15 | 15 | 50 | 65 | 2460 | 53 | 56 |

Where, $\lambda_k$ is the Eigen values and $\sum_{k=1}^{n}\lambda_k = n,\ k = 1,2,\ldots\ldots,n,\ V_{ik} = \left[a_{k1}a_{k2}\ldots\ldots a_{km}\right]^T$ is the Eigen vectors corresponding to the Eigen value $\lambda_k$.

Step 4: Finding principle components.

The uncorrelated principal component is formulated using Eq. (15).

$$Y_{mk} = \sum_{i=1}^{n} x_m(i).V_{ik} \tag{15}$$

Where, $Y_{m1}$ is the first principal component, $Y_{m2}$ is the second principal component and so on. The principal components are aligned in the descending order with respect to variance. The components with an Eigen value greater than one are chosen to replace the original responses for further analysis.

### *2.6 Hybrid optimization technique*

Current study involves integrated approach of coupling the PCA and three traditional optimization technique. PCA is used to get the weightage of each response measured from the experiments. Optimization technique like GRA, TOPSIS, and DFA were used to convert multi- responses measured during the production of industrial byproducts based concrete into single response. Current study involves weightage calculated from PCA method will be accompanied with converting multi response problem into single response problem in the GRA, TOPSIS, and DFA approach. Normalized values were used in the calculation of principal component, Eigen values and Eigen vectors. Based on principal component, Eigen values, and Eigen vectors values weightages were calculated for each response.

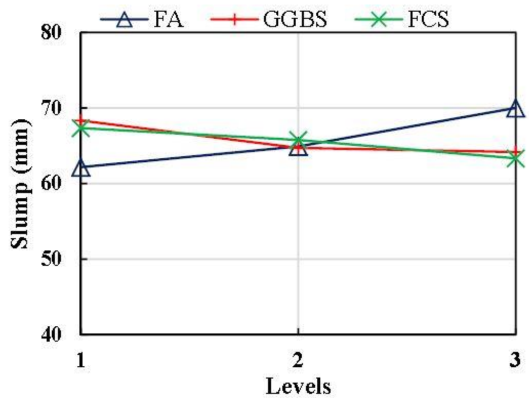


Fig. 1 Slump value of concrete with respect to different levels of replacement of FA, GGBS, and FCS

## 3. Results and discussion

In order to ascertain and to evaluate the feasibility of different industrial byproduct replacement levels, workability of fresh concrete, density, compressive strengths at 28 and 90 days have been computed and are presented in Table 8.

### *3.1 Workability*

Workability of concretes were measured in terms of slump value. Effect of different replacement levels of industrial byproducts on slump values have been tabulated in Table 8. The slump values measured were in the range of 58-77 mm. The measured slump values were in good agreement for the construction of RCC structures as per IS 456 requirement. Fig. 1 shows the mean effect of different replacement levels of industrial byproducts on workability of concrete. As the replacement level of FA increase, the slump value of concrete is also increasing. The increase in slump value is due the ball bearing effect of spherical FA particles. However, increase in levels of either GGBS or

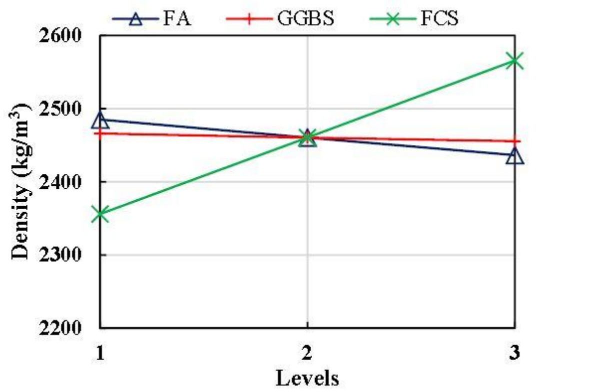


Fig. 2 Density of concrete with respect to different levels of replacement of FA, GGBS, and FCS

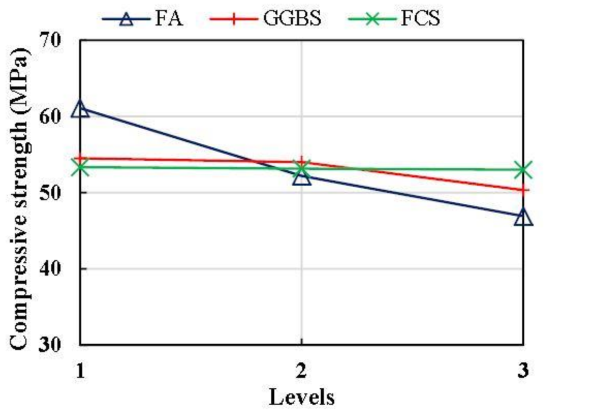


Fig. 3 Compressive strength of concrete at 28 days with respect to different levels of replacement of FA, GGBS, and FCS

FCS reduces workability of fresh concrete.

### *3.2 Density*

Density of concrete is the important parameter in structural design of RCC. As density of concrete increases dead load of structure will also increase. Due to the increase in dead load, structure need to be provided with additional reinforcement, which is uneconomical. In order to reduce density of concrete in industrial byproduct replacement Table 8 is formulated for density of concrete. The computed density values are in the range of 2333 kg/m$^3$-2591 kg/m$^3$ for different replacement levels of industrial byproducts in the concretes. Fig. 2 shows the mean effect of different replacement levels of industrial byproducts on density of concrete. As the replacement level of FCS increases, the density of concrete will also increase. The increase in density is due to the higher specific gravity of FCS. Further, decrease in density values were observed as replacement levels of FA, and GGBS increases due to lower specific gravity of FA and GGBS.

### *3.3 Compressive strength*

Table 8 presents the results of 28 and 90 days compressive strength of concrete containing GGBS, FA,

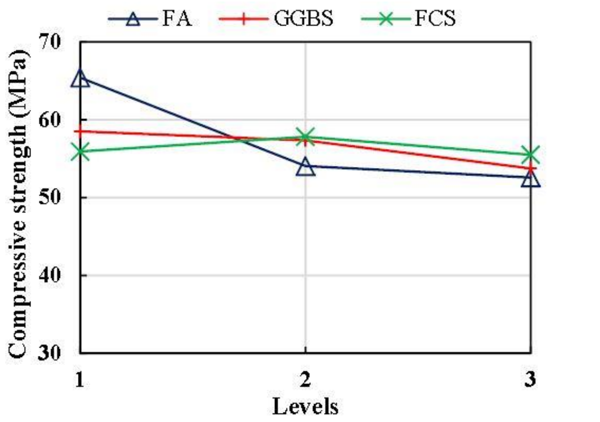


Fig. 4 Compressive strength of concrete at 90 days with respect to different levels of replacement of FA, GGBS, and FCS

and FCS. Compressive strength was in the range of 39-63 MPa, and 44-69 MPa for 28 and 90 days respectively. Figs. 3-4 shows the mean effect of different replacement levels of GGBS, FA, and FCS on compressive strength of concrete at 28 and 90 days respectively. GGBS, FCS did not show significant role in compressive strength both at 28 and 90 days. Nevertheless, compressive strength of concrete decreases slightly as the replacement of FA increases at 28 days. Due to secondary hydration reaction improvement in the compressive strength were observed in case of FA replacement at 90 days water cured concrete. Secondary hydration reaction is due to the consumption of one of the primary hydration product “calcium hydroxide” due to the “reactive silica” provided by fly ash. Further, secondary hydration reaction results in additional calcium silicate hydrate which enhances the strength property of concrete.

#### *3.4.1 Grey relational analysis (GRA)*

GRA is used to find the optimal combination of GGBS, FA, and FCS content in OPC based concrete mixture preparation. Normalization of responses were done using Eqs. (1)-(2). Maximization equations were employed for slump, compressive strength at 28 and 90 days responses. Minimization equation was employed for density. Normalized and deviation values have been tabulated in Table 9. Normalized values of responses were used for calculation of weightage of each response using PCA. PCA followed with calculation of Eigen values and Eigen vectors and are tabulated in Tables 10-11 using Eqs. (13)-(15). Weightages of each response were based on maximum of Eigen value obtained and square of the principal component values of the corresponding Eigen vectors chosen for the weightage. In the present case maximum Eigen value is found in the first principal component. So squares of Eigen vectors of first principal component values were considered as weightage of each responses. Weightage of slump, density, compressive strength at 28 days, and compressive strength at 90 days were 0.177, 0.093, 0.380, and 0.350 respectively. Further, GRC were computed using Eq. (3). PCA-GRG is determined for all the proposed mixture as explained in Eq. (4) including computed weightage of each response. In the present study, PCA-GRG should be

Table 9 Normalized and deviation values of responses in GRA.

| Run No | Normalized values | | | | Deviation values | | | |
|---|---|---|---|---|---|---|---|---|
| | Slump | Density | Compressive strength (28 days) | Compressive strength (90 days) | Slump | Density | Compressive strength (28 days) | Compressive strength (90 days) |
| 1 | 0.070 | 0.391 | 0.889 | 0.781 | 0.930 | 0.609 | 0.111 | 0.219 |
| 2 | 0.421 | 0.430 | 1.000 | 1.000 | 0.579 | 0.570 | 0.000 | 0.000 |
| 3 | 0.702 | 0.578 | 0.431 | 0.699 | 0.298 | 0.422 | 0.569 | 0.301 |
| 4 | 0.772 | 0.620 | 0.000 | 0.000 | 0.228 | 0.380 | 1.000 | 1.000 |
| 5 | 1.000 | 0.891 | 0.597 | 0.425 | 0.000 | 0.109 | 0.403 | 0.575 |
| 6 | 0.175 | 0.930 | 0.417 | 0.288 | 0.825 | 0.070 | 0.583 | 0.712 |
| 7 | 0.474 | 0.078 | 0.611 | 0.425 | 0.526 | 0.922 | 0.389 | 0.575 |
| 8 | 0.000 | 0.120 | 0.417 | 0.260 | 1.000 | 0.880 | 0.583 | 0.740 |
| 9 | 0.158 | 0.822 | 0.861 | 0.877 | 0.842 | 0.178 | 0.139 | 0.123 |
| 10 | 0.702 | 1.000 | 0.458 | 0.315 | 0.298 | 0.000 | 0.542 | 0.685 |
| 11 | 0.298 | 0.000 | 0.875 | 0.808 | 0.702 | 1.000 | 0.125 | 0.192 |
| 12 | 0.421 | 0.198 | 0.375 | 0.342 | 0.579 | 0.802 | 0.625 | 0.658 |
| 13 | 0.333 | 0.508 | 0.569 | 0.466 | 0.667 | 0.492 | 0.431 | 0.534 |
| 14 | 0.316 | 0.508 | 0.583 | 0.466 | 0.684 | 0.492 | 0.417 | 0.534 |
| 15 | 0.368 | 0.508 | 0.556 | 0.466 | 0.632 | 0.492 | 0.444 | 0.534 |

Table 10 Eigen values and explained variation in PCA-GRA

| Principal component | Eigen values | Percentage contribution of Eigen values | Cumulative percent contribution of Eigen values |
|---|---|---|---|
| 1 | 2.225 | 55.64 | 55.64 |
| 2 | 1.099 | 27.48 | 83.11 |
| 3 | 0.592 | 14.80 | 97.91 |
| 4 | 0.084 | 2.09 | 100.00 |

Table 11 Principal component analysis of results of PCA-GRA

| Performance characteristic | Principal component 1 | Principal component 2 | Principal component 3 | Principal component 4 |
|---|---|---|---|---|
| Slump | -0.421 | 0.494 | -0.756 | -0.093 |
| Density | -0.304 | 0.711 | 0.633 | 0.007 |
| Compressive strength (28 days) | 0.617 | 0.315 | -0.049 | -0.720 |
| Compressive strength (90 days) | 0.592 | 0.389 | -0.160 | 0.688 |

maximum for the optimal industrial byproduct based concrete mixture. Table 11 provides the ranking of concrete mixture with the calculation of GRC and PCA-GRG values.

### 3.4.2 Technique for order preference by similarity to ideal solution (TOPSIS)

Similar to GRA, TOPSIS approach is used to arrive at optimal mixture of GGBS, FA, and FCS based concrete. Normalization of response was carried out by using Eq. (5), and results are tabulated in Table 13. Normalized response values were used for the weightage calculation using PCA. Eigen values and Eigen vectors are tabulated in Tables 14-15, with the help of Eqs. (13)-(15). Weightage of each responses were calculated as explained in the sections. 2.5 and 3.4.1. Weightage of each responses i.e., slump, density, compressive strength of concrete at 28 days and 90 days were found to be around 0.177, 0.093, 0.380, and 0.350 respectively. Weightage obtained for each responses were used in the calculation of weighted normalized decision matrix. As explained the Eqs. 7(a)-(b), positive and negative ideal solutions were obtained. Positive and negative ideal solutions were used in the calculation of closeness coefficient. Closeness coefficient is determined by using Eqs. (8)-(9). In the present case, experimental run with higher values of closeness coefficient will be given rank 1 and considered as optimal mixture. Table 16 gives the details of weighted normalized decision matrix, positive and negative ideal solution, followed with PCA based closeness coefficient and ranking for the different experimental runs.

### 3.4.3 Desirability function approach (DFA)

Similar to GRA, and TOPSIS as explained in sections 3.4.1 and 3.4.2 respectively, DFA is also carried out to find optimal mixture. Section 2.4.3 is adopted to find optimal mixture, when GGBS, FA, and FCS were used as partial replacement to OPC, and NCA based concrete respectively. First step in DFA method to is convert actual response into individual desirability. Individual desirability calculation is based on maximization and minimization Eqs. (10)-(11). Individual desirability values are tabulated in Table 17. Further, Eigen values and Eigen vectors are presented in Tables. 18-19 which are calculated based on PCA method explained in the section 2.5. Weightage of each responses are calculated based on Eigen vector i.e principal component 1 that is obtained. Weightage of each responses i.e., slump value, density, compressive strength at 28 days, and compressive strength at 90 days are equal to 0.177, 0.093, 0.380, and 0.350 respectively. Finally, PCA based overall desirability are calculated using weightage of each response, and Eq. (12). The obtained PCA based overall desirability values are tabulated in Table 17. In the present study, PCA based overall desirability should be maximum for the optimal mixture which occupies the rank 1.

Finally, ranking reported in GRA, TOPSIS, and DFA methods are different due to the different steps and approaches. It may be noted that all three methods used for rating data analysis in the present study are well established in literature, but ranking cannot be comparable directly.

Table 12 GRC, PCA-GRG values and ranking in PCA-GRA.

| Run No | GRC | | | | PCA-GRG | Rank |
|---|---|---|---|---|---|---|
| | Slump | Density | Compressive strength (28 days) | Compressive strength (90 days) | | |
| 1 | 0.350 | 0.451 | 0.818 | 0.695 | 0.658 | 4 |
| 2 | 0.463 | 0.467 | 1.000 | 1.000 | 0.856 | 1 |
| 3 | 0.626 | 0.542 | 0.468 | 0.624 | 0.557 | 6 |
| 4 | 0.687 | 0.568 | 0.333 | 0.333 | 0.418 | 14 |
| 5 | 1.000 | 0.822 | 0.554 | 0.465 | 0.626 | 5 |
| 6 | 0.377 | 0.878 | 0.462 | 0.412 | 0.468 | 12 |
| 7 | 0.487 | 0.351 | 0.563 | 0.465 | 0.495 | 10 |
| 8 | 0.333 | 0.362 | 0.462 | 0.403 | 0.409 | 15 |
| 9 | 0.373 | 0.737 | 0.783 | 0.802 | 0.713 | 2 |
| 10 | 0.626 | 1.000 | 0.480 | 0.422 | 0.534 | 7 |
| 11 | 0.416 | 0.333 | 0.800 | 0.723 | 0.662 | 3 |
| 12 | 0.463 | 0.384 | 0.444 | 0.432 | 0.438 | 13 |
| 13 | 0.429 | 0.504 | 0.537 | 0.483 | 0.496 | 9 |
| 14 | 0.422 | 0.504 | 0.545 | 0.483 | 0.498 | 8 |
| 15 | 0.442 | 0.504 | 0.529 | 0.483 | 0.495 | 11 |

Table 13 Normalized decision matrix values of PCA-TOPSIS

| Run No | Normalized decision matrix | | | |
|---|---|---|---|---|
| | Slump | Density | Compressive strength (28 days) | Compressive strength (90 days) |
| 1 | 0.232 | 0.261 | 0.293 | 0.287 |
| 2 | 0.258 | 0.260 | 0.306 | 0.311 |
| 3 | 0.279 | 0.256 | 0.240 | 0.278 |
| 4 | 0.284 | 0.255 | 0.190 | 0.201 |
| 5 | 0.301 | 0.248 | 0.259 | 0.247 |
| 6 | 0.240 | 0.247 | 0.238 | 0.232 |
| 7 | 0.262 | 0.270 | 0.261 | 0.247 |
| 8 | 0.227 | 0.268 | 0.238 | 0.229 |
| 9 | 0.238 | 0.250 | 0.290 | 0.297 |
| 10 | 0.279 | 0.245 | 0.243 | 0.235 |
| 11 | 0.249 | 0.272 | 0.291 | 0.290 |
| 12 | 0.258 | 0.266 | 0.233 | 0.238 |
| 13 | 0.251 | 0.258 | 0.256 | 0.252 |
| 14 | 0.250 | 0.258 | 0.257 | 0.252 |
| 15 | 0.254 | 0.258 | 0.254 | 0.252 |

Table 14 Eigen values and explained variation in PCA-TOPSIS

| Principal component | Eigen values | Percentage contribution of Eigen values | Cumulative percent contribution of Eigen values |
|---|---|---|---|
| 1 | 2.225 | 55.64 | 55.64 |
| 2 | 1.099 | 27.48 | 83.11 |
| 3 | 0.592 | 14.80 | 97.91 |
| 4 | 0.084 | 2.09 | 100.00 |

Table 15 Principal component analysis of results of PCA-TOPSIS

| Performance characteristic | Principal component 1 | Principal component 2 | Principal component 3 | Principal component 4 |
|---|---|---|---|---|
| Slump | -0.421 | 0.494 | -0.756 | -0.093 |
| Density | -0.304 | 0.711 | 0.633 | 0.007 |
| Compressive strength (28 days) | 0.617 | 0.315 | -0.049 | -0.720 |
| Compressive strength (90 days) | 0.592 | 0.389 | -0.160 | 0.688 |

Therefore, a comparison is made among the rankings obtained from GRA, TOPSIS, and DFA methods. In order to check the correlation of rankings obtained from the different methods, Spearman's rank order correlation coefficients were calculated and found to be statistically significant at the 95% confidence level, indicating a positive rank order relationship among the three methods.

Spearman's rank order correlation coefficient between GRA and DFA is 0.699, between DFA and TOPSIS is 0.932, and GRA and TOPSIS is 0.704. Based on Spearmen's rankings in the TOPSIS method strongly correlated with the rankings obtained from the GRA and DFA methods. Therefore, though the results from all three methods are acceptable, the ranking obtained from the TOPSIS method is preferred.

## 4. Conclusions

Hybrid approach of RSM-PCA-GRA, RSM-PCA-

Table 16 Weighted normalized decision matrix, closeness coefficient and ranking of PCA-TOPSIS.

| Run No | Weighted normalized decision matrix using PCA | | | | D+ | D- | Cci | Rank PCA-TOPSIS |
|---|---|---|---|---|---|---|---|---|
| | Slump | Density | Compressive strength (28 days) | Compressive strength (90 days) | | | | |
| 1 | 0.041 | 0.024 | 0.111 | 0.100 | 0.016 | 0.049 | 0.758 | 3 |
| 2 | 0.046 | 0.024 | 0.116 | 0.109 | 0.008 | 0.059 | 0.883 | 1 |
| 3 | 0.049 | 0.024 | 0.091 | 0.097 | 0.028 | 0.034 | 0.551 | 4 |
| 4 | 0.050 | 0.024 | 0.072 | 0.070 | 0.059 | 0.010 | 0.150 | 15 |
| 5 | 0.053 | 0.023 | 0.099 | 0.087 | 0.028 | 0.034 | 0.543 | 5 |
| 6 | 0.042 | 0.023 | 0.091 | 0.081 | 0.039 | 0.022 | 0.357 | 12 |
| 7 | 0.046 | 0.025 | 0.099 | 0.087 | 0.029 | 0.032 | 0.526 | 6 |
| 8 | 0.040 | 0.025 | 0.091 | 0.080 | 0.041 | 0.021 | 0.340 | 13 |
| 9 | 0.042 | 0.023 | 0.110 | 0.104 | 0.014 | 0.051 | 0.790 | 2 |
| 10 | 0.049 | 0.023 | 0.092 | 0.082 | 0.036 | 0.025 | 0.415 | 10 |
| 11 | 0.044 | 0.025 | 0.111 | 0.101 | 0.102 | 0.050 | 0.328 | 14 |
| 12 | 0.046 | 0.025 | 0.089 | 0.083 | 0.038 | 0.022 | 0.364 | 11 |
| 13 | 0.044 | 0.024 | 0.097 | 0.088 | 0.029 | 0.031 | 0.515 | 8 |
| 14 | 0.044 | 0.024 | 0.098 | 0.088 | 0.029 | 0.032 | 0.521 | 7 |
| 15 | 0.045 | 0.024 | 0.097 | 0.088 | 0.030 | 0.031 | 0.509 | 9 |

Table 17 Individual and overall desirability functions of concrete with GGBS, FA, and FCS replacement

| Run No | Individual desirability | | | | Overall desirability | Rank |
|---|---|---|---|---|---|---|
| | Slump value | Density | Compressive strength (28 days) | Compressive strength (90 days) | | |
| 1 | 0.070 | 0.391 | 0.889 | 0.781 | 0.842 | 5 |
| 2 | 0.421 | 0.430 | 1.000 | 1.000 | 0.944 | 1 |
| 3 | 0.702 | 0.578 | 0.431 | 0.699 | 0.869 | 4 |
| 4 | 0.772 | 0.620 | 0.000 | 0.000 | 0.000 | 13 |
| 5 | 1.000 | 0.891 | 0.597 | 0.425 | 0.881 | 3 |
| 6 | 0.175 | 0.930 | 0.417 | 0.288 | 0.763 | 12 |
| 7 | 0.474 | 0.078 | 0.611 | 0.425 | 0.807 | 10 |
| 8 | 0.000 | 0.120 | 0.417 | 0.260 | 0.000 | 13 |
| 9 | 0.158 | 0.822 | 0.861 | 0.877 | 0.894 | 2 |
| 10 | 0.702 | 1.000 | 0.458 | 0.315 | 0.826 | 9 |
| 11 | 0.298 | 0.000 | 0.875 | 0.808 | 0.000 | 13 |
| 12 | 0.421 | 0.198 | 0.375 | 0.342 | 0.769 | 11 |
| 13 | 0.333 | 0.508 | 0.569 | 0.466 | 0.831 | 7 |
| 14 | 0.316 | 0.508 | 0.583 | 0.466 | 0.831 | 8 |
| 15 | 0.368 | 0.508 | 0.556 | 0.466 | 0.833 | 6 |

Table 18 Eigen values and explained variation in PCA-DFA

| Principal component | Eigen values | Percentage contribution of Eigen values | Cumulative percent contribution of Eigen values |
|---|---|---|---|
| 1 | 2.225 | 55.64 | 55.64 |
| 2 | 1.099 | 27.48 | 83.11 |
| 3 | 0.592 | 14.80 | 97.91 |
| 4 | 0.084 | 2.09 | 100.00 |

TOPSIS, and RSM-PCA-DFA were used to establish the optimal mixture proportion of industrial byproducts based OPC based concretes. Integrated approach established, reduces the limitation of single objective problem in multi response problem. Further, difficulties involved in weightage calculation in conversion of multi-response problem to single response problem were suitably handled with PCA method. Finally, optimal replacement level is found to be 30% GGBS, 0% FA, and 50% FCS for the production of Industrial byproducts based concrete under fresh and hardened states.

Table 19 Principal component analysis results of PCA-DFA

| Performance characteristic | Principal component 1 | Principal component 2 | Principal component 3 | Principal component 4 |
|---|---|---|---|---|
| Slump | -0.421 | 0.494 | -0.756 | -0.093 |
| Density | -0.304 | 0.711 | 0.633 | 0.007 |
| Compressive strength (28 days) | 0.617 | 0.315 | -0.049 | -0.720 |
| Compressive strength (90 days) | 0.592 | 0.389 | -0.160 | 0.688 |

## Acknowledgements

Authors would like to acknowledge National Institute of Technology Karnataka, Surathkal and MHRD for their financial support throughout the research work. Authors are also thankful to M/s Balasore alloys Ltd., Balasore, Odissa, India, for providing Ferrochrome slag.

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