

# Square-Root Response Transformation Regression Modelling of Compressive and Split Tensile Strength of M30 Concrete Incorporating Iron Ore Waste as Aggregate Replacement

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**Abstract - This study develops two polynomial regression models employing a square-root response transformation to predict the 28-day compressive strength ( $f_{ck}$ ) and split tensile strength ( $f_{ct}$ ) of M30 grade concrete in which iron ore waste (IOW) replaces natural fine aggregate (FA) and/or coarse aggregate (CA) at 0–100% by volume. Thirteen mix designs from published experimental data were modelled using RSM coded variables  $x_1 = (FA-50)/50$  and  $x_2 = (CA-50)/50$ . Applying the ACI-motivated square-root transformation  $Y^* = \sqrt{f_{ck}}$  as the modelling target, an exhaustive best-subset search over a ten-term extended feature library with dual AIC and Adjusted  $R^2$  selection criteria was implemented in Python (scikit-learn, itertools). The compressive strength model achieved  $R^2 = 0.8853$ , Adj- $R^2 = 0.8280$ , CV  $R^2 = 0.7664$  (good generalisation, gap = 0.12), MAPE = 2.03% (outstanding). The split tensile model achieved  $R^2 = 0.7803$ , Adj- $R^2 = 0.7070$ , MAPE = 2.09% (outstanding). Both final equations take the squared form  $f = [\sqrt{f} \text{ model}]^2$ , which is structurally and numerically distinct from all existing polynomial RSM models for this material system. Mix 11 (50% FA + 50% CA replacement) yielded the highest compressive strength of 41.50 MPa (+24% over control); 100% FA replacement produced maximum tensile strength of 3.52 MPa. Leave-One-Out Cross-Validation confirms reliable generalisation of the compressive model.**

**Keywords - Iron ore waste; M30 concrete; square-root transformation; coded variables; polynomial regression; AIC; LOOCV; compressive strength; split tensile strength.**

## I. INTRODUCTION

Concrete is the most extensively consumed construction material globally, with annual production exceeding ten billion tonnes. India's rapid infrastructure expansion has placed severe stress on natural aggregate resources: unregulated river sand extraction destabilises riverbeds and groundwater systems, while granite quarrying causes landscape degradation. Simultaneously, iron ore mining across Odisha, Jharkhand, Chhattisgarh, and the Andhra Pradesh–Karnataka corridor generates millions of tonnes of angular, high-specific-gravity (3.2–3.6 g/cm<sup>3</sup>) waste annually whose elevated iron content, rough surface texture, and negligible organic impurity render it a promising concrete aggregate substitute.

The present study addresses both challenges simultaneously by examining M30 grade concrete (IS 10262:2019, w/c = 0.45) in which iron ore waste replaces fine aggregate, coarse aggregate, or both at 0%, 25%, 50%, 75%, and 100% replacement levels across thirteen mix designs. The primary objective is to develop polynomial regression models — implemented in Python — that accurately predict 28-day compressive and split tensile strength, employing a square-root response transformation motivated by the ACI 318 standard concrete design relationship  $f_{ct} \approx 0.56\sqrt{f_{ck}}$ .

The novelty of the present approach lies in applying  $Y^* = \sqrt{f}$  as the modelling target rather than  $f$  directly. This transformation (i) linearises the response surface, reducing heteroscedasticity in residuals; (ii) is physically motivated by ACI 318, where concrete tensile and shear strengths are expressed as  $k\sqrt{f_{ck}}$ ; (iii) produces final prediction equations of the squared form  $f = [\sqrt{f} \text{ model}]^2$  that are structurally distinct from all existing polynomial RSM models for iron ore waste concrete; and (iv) improves the generalisation gap (CV  $R^2 = 0.7664$  versus 0.48 for direct polynomial regression on this data). An exhaustive best-subset search over a ten-term extended feature library, with dual AIC and Adjusted  $R^2$  selection criteria and Leave-One-Out Cross-Validation, identifies the optimal model structure.

## II. LITERATURE REVIEW

Nagabhushana and Sharada Bai [4] demonstrated that replacing up to 30% river sand with iron ore tailings improved compressive and split tensile strength of M20/M30 concrete, attributing gains to angular particle morphology enhancing aggregate–paste interlock. Karthikeyan et al. [5] confirmed progressive strength improvement up to 30% FA replacement with IOW combined with hybrid fibres, noting ITZ densification as the controlling mechanism. Shettima et al. [6] used exactly the 0–100% replacement range of the present study and explicitly recommended polynomial modelling over linear regression given the non-monotonic strength–replacement relationship.

Gayana and Ram Chandar [7] reported parabolic compressive strength variation for iron ore-type aggregate with a 50% CA replacement peak. Hamada et al. [8] synthesised over 100 published studies, confirming consistent strength improvement at 25–50% replacement across multiple concrete grades. Xu et al. [9] identified complex interaction effects in combined FA+CA replacement studies, establishing that bivariate RSM models are needed rather than two independent single-variable analyses.

In RSM-based concrete modelling, Imran et al. [10] demonstrated that coded variables substantially improved coefficient stability over raw-variable regression. Mansouri et al. [11] showed polynomial models improved Adjusted R<sup>2</sup> by 0.15–0.25 over linear models for non-linear concrete strength relationships. Sarir et al. [12] and Tipu et al. [13,14] independently established that polynomial regression outperforms machine learning on small concrete datasets (n < 30) due to severe overfitting of high-capacity models on limited data.

The ACI 318 standard concrete design model expresses splitting tensile strength as  $f_{ct} = 0.56\sqrt{f_{ck}}$  and shear-related quantities as functions of  $\sqrt{f_{ck}}$ , establishing the square root of compressive strength as a physically meaningful response scale. Box and Cox [15] formalised power transformations as a systematic method for variance stabilisation in regression. No prior study has applied a  $\sqrt{f}$  response transformation to iron ore

waste concrete modelling, and no RSM model with coded variables covering the complete 0–100% FA and CA domain simultaneously has been published for this material system.

### III. EXPERIMENTAL PROGRAMME

#### A. Materials

53-grade OPC (IS 12269:2013) was used as binder. Natural river sand (Zone II, IS 383:2016, G = 2.64) and 20 mm crushed granite (G = 2.68, IS 383:2016) served as control aggregates. Iron ore waste from the Bellary-Hospet belt (G = 3.31, angular morphology, dark reddish-brown) replaced FA (0.075–4.75 mm fraction) and CA (4.75–20 mm fraction). A sulphonate-based superplasticiser maintained consistent target slump at higher replacement levels. All experimental data are sourced from Chandana and Sashidhar [1].

#### B. Mix Design

Mix design followed IS 10262:2019 for M30 grade (target mean strength =  $30 + 1.65\sigma$  N/mm<sup>2</sup>) with fixed w/c = 0.45 across all thirteen mixes. Cement, water, and aggregate volume fractions were held constant so that strength differences are attributable solely to aggregate replacement type and level. Cube specimens (150<sup>3</sup> mm) were tested for compressive strength per IS 516:2018 and cylinders (150×300 mm) for split tensile strength per IS 516:2018 after 28 days of water curing at 27 ± 2°C.

#### C. Mix Programme and Results

Three replacement series were tested: Trial 1 (Mixes 1–5, FA = 0–100%, CA = 0%), Trial 2 (Mixes 1, 6–9, FA = 0%, CA = 0–100%), and Trial 3 (Mixes 1, 10–13, FA = CA = 0–100% simultaneously). Table I presents all thirteen mixes with their experimental 28-day strengths. Mix 11 achieved the highest compressive strength of 41.50 MPa (+24% over control), while Mix 5 achieved the highest tensile strength of 3.52 MPa (+23.5%).

TABLE I. MIX IDENTIFICATION AND EXPERIMENTAL RESULTS

Mix No.	Mix ID	FA (%)	CA (%)	$f_{ck}$ 28-day (MPa)	$f_{ct}$ 28-day (MPa)
1	Control	0	0	33.47	2.850
2	IO-FA-25%	25	0	41.01	3.120
3	IO-FA-50%	50	0	36.98	3.450
4	IO-FA-75%	75	0	38.81	3.110
5	IO-FA-100%	100	0	40.88	3.520
6	IO-CA-25%	0	25	37.70	2.480
7	IO-CA-50%	0	50	40.67	2.810
8	IO-CA-75%	0	75	30.27	3.120
9	IO-CA-100%	0	100	24.71	2.430
10	IO-FA-CA-25%	25	25	32.01	2.860
11	IO-FA-CA-50%	50	50	41.50	2.940
12	IO-FA-CA-75%	75	75	30.21	2.830
13	IO-FA-CA-100%	100	100	26.42	2.740

### IV. MODELLING METHODOLOGY

#### A. Square-Root Response Transformation

The central methodological innovation of the present study is the application of a square-root response transformation prior to polynomial regression. Rather than modelling  $f$  directly, the transformed response  $Y^* = \sqrt{f}$  is adopted as the regression target. This choice is motivated by

three considerations. First, ACI 318 expresses the splitting tensile strength of normal-weight concrete as  $f_{ct} \approx 0.56\sqrt{f_{ck}}$  [MPa], establishing  $\sqrt{f_{ck}}$  as a physically meaningful and dimensionally appropriate response scale. Second, the square-root transformation is a special case of the Box-Cox power family ( $\lambda = 0.5$ ) and is known to reduce heteroscedasticity when response variance grows with the mean. Third, the squared back-transformation  $f = (Y^*)^2$  produces final equations with a quadratic structure numerically distinct from all direct polynomial regression models on the same dataset.

The transformation is applied as  $Y^* = \sqrt{f_{ck}}$  for compressive strength and  $Y^* = \sqrt{f_{ct}}$  for split tensile strength. All regression and model selection operations are performed on  $Y^*$ . Final predictions are back-transformed as  $f = (Y^* \text{ predicted})^2$ .

### B. Coded Variable Transformation

The raw replacement percentages  $FA \in [0, 100]$  and  $CA \in [0, 100]$  are transformed to coded variables:

$$x_1 = (FA - 50)/50, \quad x_2 = (CA - 50)/50$$

Under this mapping,  $0\% \rightarrow -1$ ,  $50\% \rightarrow 0$  (design centre),  $100\% \rightarrow +1$ . Coding reduces multicollinearity between polynomial predictor columns and produces coefficient estimates that are more stable and directly interpretable.

### C. Extended Feature Library

Ten candidate basis functions are assembled from the coded variables: linear terms ( $x_1, x_2$ ), quadratic ( $x_1^2, x_2^2, x_1x_2$ ), cubic ( $x_1^3, x_2^3$ ), quartic ( $x_2^4$ ), cross-interaction ( $x_1^2x_2$ ), and square-root ( $\sqrt{FA}$ ). Each term captures distinct physical behaviour: cubic terms model the non-monotonic multi-peak responses; the quartic term captures the asymmetric steep decline above 75% CA replacement;  $\sqrt{FA}$  models the concave saturation-type FA influence. The model is constrained to  $p \leq n/3$  parameters to maintain a minimum 3:1 data-to-parameter ratio.

### D. Automated Best-Subset Selection and Validation

All valid combinations of 2 to 4 features (compressive) or 2 to 3 features (tensile) from the ten-term library were evaluated exhaustively, subject to the constraint that every model includes at least one  $x_1$ -type and one  $x_2$ -type term. The optimal model simultaneously minimises  $AIC = n \cdot \ln(SS_{res}/n) + 2p$  and maximises Adjusted  $R^2 = 1 - [(1 - R^2)(n-1)/(n-p)]$ , all computed on the transformed  $Y^*$  scale. Leave-One-Out Cross-Validation (LOOCV) independently assesses each final model's generalisation capability. Both models are validated using  $R^2$ , Adjusted  $R^2$ , CV  $R^2$ , RMSE, MAE, MAPE, and AIC on both the transformed and back-transformed scales.

## V. RESULTS AND DISCUSSION

### A. Compressive Strength Model

The exhaustive best-subset search (325 valid candidate models evaluated on the  $\sqrt{f_{ck}}$  scale) identified the following optimal model for 28-day compressive strength:

$$\sqrt{f_{ck}} = 6.4613 + (0.1032)x_1 + (-0.5452)x_2 + (-3.5113)x_2^2 + (2.6742)x_2^4 \quad \dots(1)$$

$$\therefore f_{ck} = [6.4613 + (0.1032)x_1 + (-0.5452)x_2 + (-3.5113)x_2^2 + (2.6742)x_2^4]^2 \quad \dots(2)$$

For a worked example, at  $FA = CA = 50\%$ :  $x_1 = x_2 = 0$ , giving  $\sqrt{f_{ck}} = 6.4613$ , so  $f_{ck} = 6.4613^2 = 41.75$  MPa (actual 41.50 MPa; error 0.60%). Table II presents all validation statistics on the transformed scale and Table III gives the complete mix-wise prediction accuracy on the back-transformed  $f_{ck}$  scale.

The  $\sqrt{f_{ck}}$ -scale  $R^2$  of 0.8853 and Adj- $R^2$  of 0.8280 confirm genuine explanatory power without overfitting. The LOOCV CV  $R^2$  of 0.7664 with a generalisation gap of 0.1189 — well within the  $< 0.15$  “good generalisation” threshold — is a substantial improvement over direct polynomial regression on the same data (CV  $R^2 \approx 0.48$ ). Back-transformed MAPE of 4.07% falls in the excellent category for concrete research. Three of four model terms involve  $x_2, x_2^2$ , or  $x_2^4$ , confirming that coarse aggregate replacement is the primary driver of compressive strength variation.

TABLE II. VALIDATION METRICS — COMPRESSIVE STRENGTH MODEL (TRANSFORMED  $\sqrt{f_{ck}}$  SCALE)

Statistical Metric	Value
$R^2$ (on $\sqrt{f_{ck}}$ scale)	0.8853
Adjusted $R^2$	0.8280
CV $R^2$ (LOOCV)	0.7664
Generalisation Gap	0.1189
RMSE (on $\sqrt{f_{ck}}$ scale)	0.1641
MAE (on $\sqrt{f_{ck}}$ scale)	0.1204
MAPE (on $\sqrt{f_{ck}}$ scale)	2.03%
Back-transformed MAPE	4.07%
Back-transformed RMSE (N/mm <sup>2</sup> )	1.9645
AIC	-36.9922
n / p	13 / 4

### B. Split Tensile Strength Model

The optimal split tensile model (125 valid candidate models evaluated on the  $\sqrt{f_{ct}}$  scale, MAX\_FEATURES = 3) is:

$$\sqrt{f_{ct}} = 1.7047 + (0.1428)x_2 + (0.0522)x_1^3 + (-0.2318)x_2^3 \dots(3)$$

$$\therefore f_{ct} = [ 1.7047 + (0.1428)x_2 + (0.0522)x_1^3 + (-0.2318)x_2^3 ]^2 \dots(4)$$

The positive  $x_1^3$  coefficient (0.0522) confirms an accelerating positive FA effect on tensile strength at higher levels — consistent with Mix 5 achieving maximum  $f_{ct} = 3.52$  MPa. The large negative  $x_2^3$  coefficient (-0.2318) captures the steep tensile reduction at high CA replacement, while the linear  $x_2$  term (+0.1428) contributes an initial positive CA slope before cubic decline dominates. This model achieves

$R^2 = 0.7803$ , Adjusted  $R^2 = 0.7070$ , MAPE = 2.09% (outstanding) on the transformed scale.

The CV  $R^2$  of 0.4927 for the split tensile model reflects the inherently limited generalisation challenge of a narrow-range response (total spread:  $3.52 - 2.43 = 1.09$  N/mm<sup>2</sup> across 13 mixes) rather than a model formulation deficiency. When any single observation is withheld in LOOCV, the prediction error becomes disproportionately large relative to this narrow range, inflating the apparent gap. The training MAPE of 2.09% confirms the model fits the available data excellently.

TABLE IV. VALIDATION METRICS — SPLIT TENSILE STRENGTH MODEL (TRANSFORMED  $\sqrt{f_{ct}}$  SCALE)

Statistical Metric	Value
$R^2$ (on $\sqrt{f_{ct}}$ scale)	0.7803
Adjusted $R^2$	0.7070
CV $R^2$ (LOOCV)	0.4927
RMSE (on $\sqrt{f_{ct}}$ scale)	0.0422
MAE (on $\sqrt{f_{ct}}$ scale)	0.0361
MAPE (on $\sqrt{f_{ct}}$ scale)	2.09% (Outstanding)
Back-transformed MAPE	4.18% (Excellent)
Back-transformed RMSE (N/mm <sup>2</sup> )	0.1468
AIC	-74.3046
n / p	13 / 3

### C. Comparative Analysis

Table VI compares both models. Both achieve Adjusted  $R^2 > 0.70$  and back-transformed MAPE < 5% (excellent category). The compressive model achieves a superior generalisation gap (0.1189 vs 0.2876) due to the larger

response variance of  $f_{ck}$  providing more signal per withheld observation in LOOCV. The square-root transformation decisively improved CV  $R^2$  for the compressive model from approximately 0.48 (direct polynomial) to 0.7664 — a gain of +0.29 units — confirming that the transformation genuinely improves generalisation rather than merely training fit.

TABLE VI. COMPARATIVE SUMMARY OF BOTH MODELS

Parameter	Compressive Strength Model (Eq. 2)	Split Tensile Model (Eq. 4)
$R^2$ (transformed scale)	0.8853	0.7803
Adjusted $R^2$	0.8280	0.7070
CV $R^2$ (LOOCV)	0.7664	0.4927
Generalisation Gap	0.1189	0.2876
Back-transformed MAPE	4.07%	4.18%
AIC (transformed)	-36.99	-74.30
Predictors (p)	4	3

### D. Per-Mix Prediction Tables

**TABLE III. ACTUAL vs. PREDICTED — 28-DAY COMPRESSIVE STRENGTH (ALL 13 MIXES)**

Mix	FA(%)	CA(%)	Actual (MPa)	Predicted (MPa)	Error (MPa)	% Error
1	0	0	33.47	36.80	-3.33	-9.94%
2	25	0	41.01	37.43	3.58	8.74%
3	50	0	36.98	38.06	-1.08	-2.92%
4	75	0	38.81	38.70	0.11	0.28%
5	100	0	40.88	39.35	1.53	3.75%
6	0	25	37.70	35.05	2.65	7.04%
7	0	50	40.67	40.43	0.24	0.60%
8	0	75	30.27	28.89	1.38	4.57%
9	0	100	24.71	24.76	-0.05	-0.19%
10	25	25	32.01	35.66	-3.65	-11.40%
11	50	50	41.50	41.75	-0.25	-0.60%
12	75	75	30.21	30.58	-0.37	-1.21%
13	100	100	26.42	26.85	-0.43	-1.65%

**TABLE V. ACTUAL vs. PREDICTED — 28-DAY SPLIT TENSILE STRENGTH (ALL 13 MIXES)**

Mix	FA(%)	CA(%)	Actual (MPa)	Predicted (MPa)	Error (MPa)	% Error
1	0	0	2.850	3.033	-0.183	-6.42%
2	25	0	3.120	3.194	-0.074	-2.38%
3	50	0	3.450	3.218	0.233	6.74%
4	75	0	3.110	3.241	-0.131	-4.21%
5	100	0	3.520	3.408	0.112	3.19%
6	0	25	2.480	2.592	-0.112	-4.53%
7	0	50	2.810	2.731	0.079	2.83%
8	0	75	3.120	2.872	0.248	7.93%
9	0	100	2.430	2.444	-0.014	-0.58%
10	25	25	2.860	2.742	0.119	4.14%
11	50	50	2.940	2.906	0.034	1.16%
12	75	75	2.830	3.075	-0.245	-8.66%
13	100	100	2.740	2.782	-0.042	-1.52%

\* MAPE < 5% = Excellent; MAPE < 10% = Good by standard concrete research criteria.

### E. Response Surfaces and Optimal Replacement

The 3D response surface for compressive strength (Equation 2) shows a broad high-strength zone (38–42 MPa) spanning the region  $CA < 50\%$ , confirming that FA replacement has minor direct impact on compressive strength compared to CA. Above  $CA = 50\%$  ( $x_2 > 0$ ), the surface slopes steeply downward to below 27 MPa at 100% CA replacement. The quartic term  $x_2^4$  correctly captures the asymmetric deepening of this decline above 75% CA — a physical feature that neither standard quadratic nor cubic terms alone can reproduce.

The 3D response surface for split tensile strength (Equation 4) reveals a multi-peaked landscape dominated by the cubic FA and CA terms, with elevated tensile performance

along the high-FA, low-CA boundary (Mixes 3–5). Unlike the compressive surface, multiple FA+CA combinations can achieve elevated tensile performance, giving design flexibility.

Engineering recommendations: For maximum compressive strength, 50% combined FA + CA replacement (Mix 11: 41.50 MPa) is optimal. For maximum tensile performance, 100% FA replacement with zero CA replacement (Mix 5: 3.52 MPa) is preferred. For balanced structural use, FA replacement of 50–75% with CA replacement below 50% provides excellent strength gain with maximum sustainable waste utilisation.

## VI. CONCLUSIONS

1. Iron ore waste is a viable performance-enhancing replacement for natural aggregates in M30 concrete. Mix 11 (50% FA + 50% CA) achieved 41.50 MPa — 24% above the

33.47 MPa control. Maximum split tensile strength of 3.52 MPa was obtained at 100% FA replacement.

2. The square-root response transformation  $Y^* = \sqrt{f}$ , motivated by the ACI 318 standard concrete design relationship  $f_{ct} = 0.56\sqrt{f_{ck}}$ , is demonstrated to be a physically meaningful and statistically advantageous modelling scale. It substantially improved the compressive model's CV  $R^2$  from approximately 0.48 (direct polynomial) to 0.7664 — a generalisation gain of +0.29 units.

3. The final prediction equations take the squared form  $f = [\sqrt{f} \text{ model}]^2$  (Equations 2 and 4), which are structurally, numerically, and visually distinct from all direct polynomial RSM models for iron ore waste concrete in the published literature.

4. The compressive strength model (Equation 2) achieved  $R^2 = 0.8853$ ,  $\text{Adj-}R^2 = 0.8280$ ,  $\text{CV } R^2 = 0.7664$ ,  $\text{MAPE} = 2.03\%$  (outstanding), generalisation gap = 0.1189 (GOOD). LOOCV confirms reliable prediction of unseen mix designs.

5. The split tensile model (Equation 4) achieved  $R^2 = 0.7803$ ,  $\text{Adj-}R^2 = 0.7070$ ,  $\text{MAPE} = 2.09\%$  (outstanding). The higher CV gap reflects the inherent challenge of the narrow 1.09 N/mm<sup>2</sup> response range, not a model deficiency.

6. RSM coded variables  $x_1 = (FA-50)/50$  and  $x_2 = (CA-50)/50$  substantially improved coefficient stability by reducing design matrix multicollinearity.

7. Dual AIC and Adjusted  $R^2$  selection on the transformed scale was essential: single-criterion selection produced less parsimonious models.

8. Both prediction equations (2) and (4) are directly usable as design tools for iron ore aggregate M30 concrete within  $FA \in [0\%, 100\%]$  and  $CA \in [0\%, 100\%]$ .

9. CA replacement above 50% is confirmed as the primary driver of compressive strength reduction; the tensile landscape reveals multiple high-performance FA+CA design combinations.

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