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Research Article

OPTIMIZATION OF G+2 RESIDENTIAL BUILDING USING MACHINE LEARNING

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ABSTRACT

Telangana is the twelfth maximum populous country in India in phrases of populace. Single-own circle of relative's houses are maximum typically called houses or houses. An condominium residence with a couple of housing devices is referred to as a two-own circle of relatives' residence or an condominium residence. Mansion is a resident-owned, non-condo condominium. The production area is of specific significance nowadays because of India's young populace and the resultant boom in housing demand. Land costs are skyrocketing because of growing housing demand. As a result, fabric costs also are growing. Limited homes and residing areas must additionally be considered. Every day, significant fee will increase because of inflation are impacting extra production costs. Optimization strategies are presently achieved with the aid of using fixing complicated mathematical necessary and differential equations. Structure weight-based optimization has many realistic benefits in all regions of the technology. In the sphere of civil engineering, weight-optimized additives are less expensive and clean to move to production sites. In this study, gadget studying optimizations have been advanced to optimize the load of the rebar taking into consideration factors of shape, size, and topology. This studies paper introduces gadget studying (ML) to optimize the price of designing and building the constructing potential of a specific home. Machine studying (ML) makes use of operations that mimic herbal evolutionary operations consisting of reproduction, crossover, and mutation to progressively enhance the answer of next populations and bring advanced progeny growth. Global seek method. In this work, a pc software has been advanced to boost the layout of strengthened concrete homes at minimum price. The plan consists of the appearance of the (ML) layout and the readiness of the goal feature. Then, with numerous constraints applied, the changed goal feature arrives. This will calculate the changed price of the required fabric. Concrete and reinforcement, and parametric studies are managed.

INTRODUCTION

This paper offers a brand new optimization technique for the layout of bolstered concrete (RC) systems. Optimal sizing and reinforcement of columns in multi span and multi storey RC systems consists of highest quality stiffness correlations among structural elements, saving fees over conventional previous artwork layout solutions.

With all of the engineering necessities for designing beams, columns, slabs, and foundations with many suited pass sections, maximum engineers have the proper pass segment to reduce fees without similarly calculations. I have. Don't hesitate to pick out to increase. This report permits engineers to apply layout optimization fashions to effortlessly pick the proper dimensions for additives and reduce the value of concrete, steel, and systems.

Following latest tendencies within side the area of RC structural layout optimization during the last decades, many researchers have used mathematical and evolutionary seek strategies to optimize the layout as a characteristic of the aggregate of gravity and lateral load. I used it. I attempted it. Upon arrival, Krishnamurthy and Munro used linear programming to optimize the bolstered concrete frame. Originally advanced via way of means of Francis Galton, linear regression is extensively utilized in predictive analytics and Modelling. Once you already know the peak of someone, you could use equations to expect that person's weight. This instance predicts the load of someone whilst he's tall. This easy linear regression examines the impact of unbiased variables at the results. These researchers essentially set structural parameters consisting of cloth properties, boundary conditions, and structural length as inputs to the linear

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regression version to expect the capacity of the shape to resist loads. Due to its significance withinside the industry, optimization of concrete systems has been the difficulty of a few preceding research. A thorough literature assessment in this difficulty is past the scope of this article, however a few wonderful optimization research are in brief stated here. For instance, Balling and Yao (1997) and Mohar Rami and Grierson (1993) used nonlinear programming (NLP) strategies in RC frames to realistically spherical non-stop values of beams, columns, and shear wall elements. Rice area. I changed into searching out a solution ordered via way of means of an order of magnitude.

This look at implements an set of rules that could generate value-optimized designs for RC systems primarily based totally on practical value facts for materials, modeling, and staff even as assembly all ACI 318 05 code and layout overall performance necessities increase. This optimization system is proven in a layout instance that examines the impact of stiffness distribution at the highest quality span of a portal frame, the highest quality quantity of columns for a selected span, and the highest quality length of a composite shape. gain. RS way concrete and stone value facts to get a sensible value relying on the scale of the structural element.

Residential Building

A dwelling is a detached house or a block of an apartment, or a building with or less on the 3rd floor or less above ground. However, when applied to a building within the boundaries of a municipality with a population of 1 million or more, "dwelling" means a building that includes dwelling units on the 4th floor or lower above the ground. Residents are mostly permanent.

Minimizing energy consumption and life cycle cost are two key factors in home construction. Therefore, in order to achieve the optimum shape with the best performance, we combined a new optimization simulation method called "Enhanced Emperor Penguin Optimizer" with a building energy simulation tool called “Quest” to minimize the energy consumption of the house. Suppress to. A comprehensive list of envelope criteria to consider.

In general, the model optimization process can reduce computational time and cost. Comparing the particle swarms, the applied method works very well and is very close to the optimal in less than 50% of the simulation. Population growth and increasing demand from the local economy for new buildings are considered to be the largest contributors to green house gas emissions. Therefore, improving the energy efficiency of the building sector has become an important goal not only for the construction of fossil fuels, but also for the reduction of gas emissions. One of the most effective approaches to reducing CO_2 emissions and energy consumption in new buildings is to consider the energy efficiency of

METHODOLOGY

The machine learning optimization approach consists of applying three consecutive steps:

1. Use Energy Plus to build an energy model (basic model), sample input parameters and perform energy simulations. 2) Introduce simulated I / O relationships when features / labels and models are incorporated into the ML algorithm. 3) Bayesian black box optimization to minimize the total power consumption of for the energy consumption of the building. Define design variables in the minimum- maximum range, run input samples with a uniform distribution, get a set of samples and Energy Plus input files, and create a database for training ML- based predictive models. Generated from the value. All of these files were then evaluated / simulated in Energy Plus. At this point, I used a custom Python script to automate both the process that generated the input file and the reading of the Energy Plus output file from the associated simulation run.

Objective Function

Minimized targeting functionality is calculated for identity tagging. This function calculates the total frame value. In addition to the unit price, it is expressed by the volume of concrete, the weight of steel, and the proximity of the formwork to the slab.

The total cost of a reinforced concrete airframe can be expressed as:

$$\mathbf{Cost = C\ beam + C\ column + C\ slab + C\ footing}$$

$$C_{\text{columns}} = C_c\, n_c \sum_{i=1}^{NS} (V_{cc} - V_{cs} - V_l)_i + C_s\, n_c\, \gamma_s \sum_{i=1}^{NS} (V_{cs} + V_l)_i + C_l\, n_c \sum_{i=1}^{NS} (A_{cl})_i$$

$$C_{\text{beams}} = C_c\, n_b \sum_{i=1}^{NS} (V_{bc} - V_{bs} - V_v)_i + C_s\, n_b\, \gamma_s \sum_{i=1}^{NS} (V_{bs} + V_v)_i + C_l\, n_b \sum_{i=1}^{NS} (A_{bl})_i$$

$$C_{\text{slabs}} = C_c\, n_s \sum_{i=1}^{NS} (V_{sc} - V_{ss} - V_l)_i + C_s\, n_s\, \gamma_s \sum_{i=1}^{NS} (V_{ss} + V_l)_i + C_l\, n_s \sum_{i=1}^{NS} (A_{sl})_i$$

$$C_{\text{footings}} = C_c\, n_f \sum_{i=1}^{NS} (V_{fc} - V_{fs} - V_l)_i + C_s\, n_f\, \gamma_s \sum_{i=1}^{NS} (V_{fs} + V_l)_i + C_l\, n_f \sum_{i=1}^{NS} (A_{fl})_i$$

Where

Include accurate energy predictions for optimal decision making.

C column = cost of column for the whole frame
C beam = cost of beam for the whole frame
C slab = cost of slab for the whole frame
C footing = cost of footing for the whole frame
C_C = cost of concrete per unit volume.
C_S = cost of steel, ties, and stirrups per unit weight. C_f = cost of framework per unit surface area.
N_S = numbers of stories
N_C = numbers of columns per story. N_b = numbers of beams per story
γ_S = unit weight of steel.
V_{CC} = Volume of concrete in a column, calculated by using equation

V_{cs} = Volume of longitudinal reinforced steel in a column, calculated by using equation.

V_i = Volume of lateral ties in a column, calculated by using equation.

A_{cl} = surface area of formwork for a column.

V_{bc}= volume of concrete in a beam, calculated by using equation.

V_{bs}= volume of tensile reinforced steel in a beam, calculated using equation.

V_{ss} = volume of tensile reinforced steel in a slab, calculated using equation.

V_{fs} = volume of tensile reinforced steel in a footing, calculated using equation.

A_{bl} = surface area of framework for a beam

A_{sl} = surface area of framework for a slab

A_{fl} = surface area of framework for a footing

General Description

1. Type of Building – G +2 Residential Building
2. Number of storey - 2 Storey
3. Types of foundation – Shallow foundation
4. Height of building – 9m from G.L
5. Total gross area of the building – 138.88 sq.m
6. Column Size – 230 x 300 & 230 x 460 mm
7. Beam Size – 230 x 300 & 230 x 460 mm
8. Slab thickness – 150mm
9. Footing Size – 1220 x 1220 x 1000mm

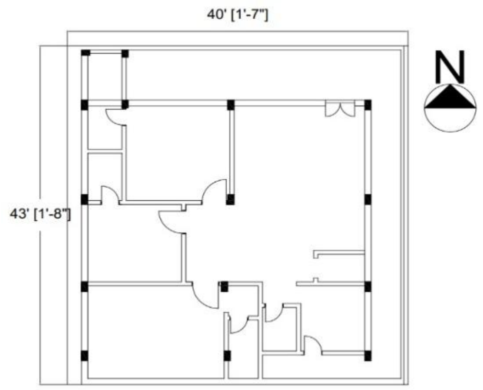

Fig 1 Structural Drawing

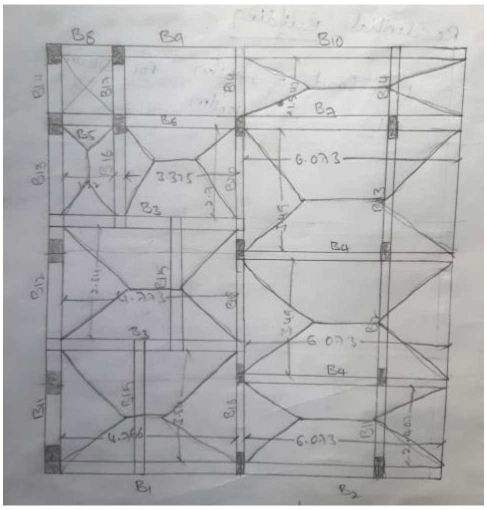

Fig 2 Beams and Columns Loading distribution

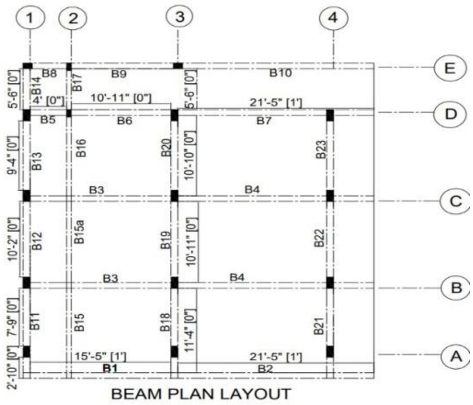

Fig 3 Beams Positions

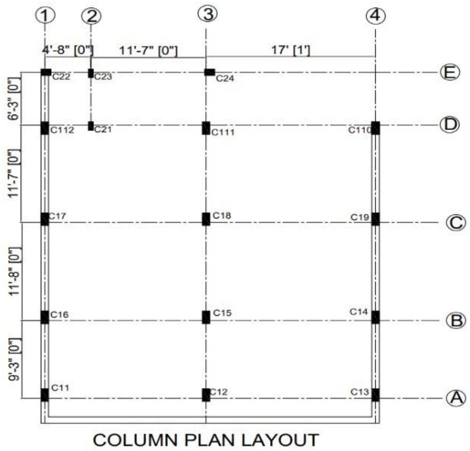

Fig 4 Column Position

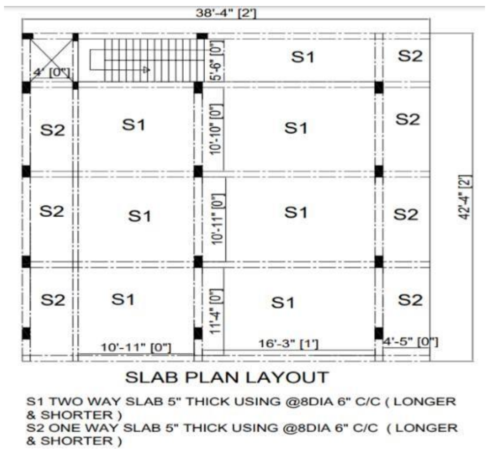

Fig 5 Slab Position

Design Criteria

Concrete Grade: M20 N/mm^2

Steel Grade: Fe 415 N/mm^2

Overall depth Slab: 150mm

Dead loads

Unit Weight of the Concrete: 25 KN/m^3

Unit Weight of the Brick: 20 KN/m^3

Self-weight of the Beam: 2.97 KN/m Self-weight of the Column: 0.793 KN/m Self-weight of the Slab: 6.192 KN/m Floor Finish: 1 KN/m^2

Live loads

For Residential Building: 2 KN/m^2

Design of Slabs

Given data

Effective Shorter Span (Lx) = 2.103m Effective Longer Span (Ly) = 3.84m Width of Support = 0.23m
Fck = 20 N/mm2
Fy = 415 N/mm2

Step 1: Type of Slab:

Ly/Lx = 3.84/2.103
= 1.82< 2
Since Ly/Lx ratio is lesser than 2
The slab should be designed as two-way
Slab

Step 2: Depth of Slabs

Clear cover = 25 mm
Adopt effective depth (d) = 125mm
Over all depth (D) = 150mm

Step 3: Loads

Self-weight of slab = 6.192 KN/m2
Live load = 2 KN/m2
Floor finish = 1 KN/m
Total load = 9.192 KN/m2
Factored load (Wu) = (1.5 X 6.192) = 9.288 KN/m2

Step 4: Maximum Bending Moment

From IS 456, Table 26
Short span coefficient
αx (-ve) = 0.0418
αx(+ve) = 0.0312
Long span coefficient

αy(-ve) = 0.032
αy(+ve) = 0.024

Mux(+ve) = $\alpha x W l x^2$ = (0.0418×9.288 × 2.103) = 0.816 KN-m

Mux(-ve) = $\alpha x W l x^2$ = (0.0312×9.288 × 2.103) = 0.609KN-m

Muy(+ve) = $\alpha y W l x^2$ = (0.024x9.288 × 2.103) = 0.468 KN-m

Muy(-ve) = $\alpha y W l x^2$ = (0.032×9.288 × 2.103) = 0.625 KN-m

Step 5: Check for depth

From IS 456, Pg.no:96
Mu.lim = 0.36Xu,max/d (1-0.42 Xu,max/d)bd2fck
= 0.36x0.48x(1-(0.42x0.48)) x1000x(125)2x20
Mu, lim = 43.11x106 KN-m
Mu, actual < Mu, lim
Hence section is under reinforced Hence safe

Step 6: Calculations of Reinforcement

Shorter Span

Mu = 0.87 fy Ast x d(1 −Ast fy bd fck)
0.816x106 = 0.87x415x Ast x 125x(1 - Ast ×415 1000×125×20)
Ast, Req = 481.92 mm2
Use 10mm φ bars,
Sv = 50.26/481.92 × 1000
Sv = 104.29mm
Provide 8mm φ bars @104mmc/c
Ast, prov = 120 mm2

Longer Span

Mu =0.87 fy Ast d(1 – Ast fy bd fck)
0.468x106 = 0.87x415x Ast x 125x (1 – Ast ×415 1000×125×20)
Ast =481.92 mm2
Use 10mm φ bars,
Sv = 50.26/481.92 × 1000
= 104.29 mm
Provide 8mm φ bars @ 104 mmc/c
Ast, prov = 120 mm2

Design of Beams

Step 1: **Given Data** Effective Length = 11.26 m Width = 230 mm
Depth = 435 mm
Cover = 25 mm
D = 460 mm
Grade of Concrete = M20
Grade of Steel = Fe415
= 250 mm
Provide 4 nos. of 16 mm dia. bars @ 250 mm c/c

Step 6: Check for shear

Vu = 89.61 KN
τv = Vu/b x d = 24389/230× 435
= 0.243 N / mm2
τc = 0.4 N / mm2 ,τc max = 2.8 N / mm2 τc max > τc > τv
Shear Reinforcement should be provided.
Vus = 0.87 × fy x Asv x d / Sv
Sv = 0.87 × 415 ×250 × 435 /89.61×10^3= 438 mm Provide 10mm dia. of 2 Legged Stirrups @ 400 mm c/c
Step 7: Check for Spacing
Sv ≤ (0.75 d) = 0.75 x 435 = 326 mm
Sv ≤ (Asv x fy /0.4 x b)
Sv= (250 ×415/ 0.4 × 230) = 1127 mm
Sv ≤ 300 mm
Hence ok

Design of Columns

Use M20 grade Concrete and FE415 grade Steel. Length, L = 3m
Size = 460 x 230 mm & 300 x 230 mm

Step 2: Load Calculations

Dead Load from slab = 1 KN / m2
Wall Load = 0.23 x 20 x 3 = 13.8 KN/m
Self-Weight of beam = 0.23 x 0.435 x 25 = 2.5 KN/m
Live Load = 2 KN/m
Total Dead Load (Wd) = 21.66 KN/m

Step 3: Ultimate Bending moment and Shear

Mu support = 1.5 x (Wd x l2)/12
= 1.5x (21.66 × $(11.26)^2$ /12
= 343.27 KN-m

Step 4: Check for Depth

d = √ Mu /(0.136 ×fck x b)
= √ 343.27 × 10^6 /(0.136 ×20 × 230)
= 740 mm $d_{provided} > d_{required}$
Hence OK

Step 5: Area of Steel

At Support

C min = + 500 30
Load = 1200KN

Factored load = 1.5 x 1200 = 1800 KN

Step 1: Calculation of Ac

By assuming % of Steel as 1% of cross area
Asc = 1/100 x Ag = 0.01Ag
Ag = Asc + Ac Ac = Ag - Asc Ac = 0.99 Ag.

Step 2: Calculation of Dimensions of Column

Pu = 0.45 fck Ac + 0.67 fu Asc
1200 x 10^3 = 0.45 x 20 x 0.99 Ag + 0.67 x 415 x 0.01
Ag = 153971.173 mm2
By using Rectangular Column with Area of a^2
A^2 = 153971.173 mm^2
A = 392 mm
Take a as 400 mm

Emin = $\frac{3500}{} + \frac{400}{} \geq 20$
Hence Safe

Step 3: Calculations of Area of main steel Ac

Pu = 0.4 fck Ac + 0.67 fu Asc
Ag = Ac + Asc
Ac = Ag – Asc
1800 x 103 = 0.4 x 20 x (153971.173 – Asc) + 0.67 415 x Asc
Asc = 153.711 mm^2
Take 1540 mm^2
By taking 16 mm dia bars
1 bar = π/ 4 x $(16)^2$ = 201 mm^2
Numbers of bars = 1540/ 201 = 7.66
So, take 8 bars of 16 mm dia bar

Step 4: Calculation of transverse reinforcement

16 d = 16 x 16 = 256mm
Min lateral dimensions = 400 mm
300mm
So, c/c distance between ties 256mm
Dia of bar
0.25 x d = 0.25 x 16 = 4 mm
5 mm
So, take 8 mm dia bar
Final reinforcement use 8 bars of 16mm dia main and 8 bars of 250 mm distance ties.

Design of Footing

Given Data

Size of the column =230x460mm Load on the column Wu = 263.5 KN Safe bearing capacity of soil, q_o = 571.08 KN/mm2
fck = 20N/mm2 fy = 415N/mm2

Step 1: Size of footing

Load on column = 263.5 KN
10 % of column axial
Load for footing = 10% (263.5)
= 263.5 +160
= 423.5 KN
Area of footing = load on footing / SBC
= 423.5 / 200
= 2.1 m
So, we can take 2.1 x 2.1 m

Step 2 Net upward pressure *Stress = force / area*

= 1.5 x total load on footing / area of footing
= 1.5 x 423.5 / 2.1 x 2.1
= 144.04KN /m2

Step 3 Bending moment

@critical section of the footing critical section @
Force of column from the edge of column
2100/2 – 230 /2 = 935 mm
Load on critical section = stress x bf
= 144.04 x 230
= 302.5 KN /m
Bending moment = Wl^2 / 2 = 302.5 x $(0.82)^2$ /2
= 124.025 KN.m
1800 x 103 = 0.4 x 20 x (153971.173 – Asc) + 0.67 415 x Asc
Asc = 153.711 mm^2
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= 302.5 KN /m
Bending moment = Wl^2 / 2 = 302.5 x $(0.82)^2$ /2
= 124.025 KN.m

Estimation

Table 1 Estimation

S.NO	Description	Quentity	Amount
1	Earthwork Excavation	96 Ft	1,24,800
2	Concrete	110.56 Cub.m	6,72,312
3	Steel	11035.72 Kgs	8,12,875
4	Bricks	6768.57 Sq.ft	3,79,040
5	Plastiring	4073.03Sq.ft	1,26,264
6	Painting	-	1,22,190
7	Laboures Cost	-	4,32,000
8	10% Contract Profit	-	2,66,048
	Total	-	**29,35,529**

Total Cost = 29,35,529 /-

Machine learning model

The model's parameters are the constituent variables inside the model, and their values can be estimated from the specified data.

- Requirements in the model for prediction.
- There is a function in the problem definition model.
- You are estimated or learned from the data.
- In many cases, prediction is not set manually.
- Usually saved as part of a trained model

Therefore, point-to-point are important parameters for machine learning algorithms. This is also part of model learned from past training data. The specific models used in machine learning are the functions and parameters needed to make predictions for new data. Whether a model has fixed parameters or variables determines whether the model can be said to be parametric or non-parametric.

Machine Learning

Machine learning (ML) is a type of artificial intelligence (AI) that allows you to predict outcomes more accurately, even if your software application is not explicitly programmed. Thus, machine learning algorithms use historical data as input to predict new output values. Recommended motor is a general use case for the machine study. Other popular uses include fraud detection, spam filtering, malware threat detection, business process automation, and predictive maintenance. Machine learning is important because it provides companies with an overview of customer behaviour trends and operates samples to aid in new product development. Many large companies today, such as Facebook, Google, and Uber, have machine learning technology at the core of their business. Machine learning has become an important competitive factor for many companies.

In statistical Modelling, regression analysis is a set of statistical procedures for estimating the relationship between a dependent variable and one or more independent variables. The most common form of regression analysis is linear regression, where one finds the line that best fits the data according to a particular mathematical criterion. First, regression analysis is widely used for prediction and forecasting, where its use overlaps significantly with the field of machine learning. Second, in some cases, regression analysis can be used to infer a causal relationship between independent and dependent variables.

XG Boost is a synthetic machine learning algorithm based on a decision tree using a scoring framework. In prediction problems involving unstructured data, artificial neural networks tend to outperform all other algorithms or frameworks. XG Boost stands for Extreme Grading Boosting. It uses more precise approximations to find the best tree model. Boost: N new training datasets are formed by replacing random sampling from the original data set, where some observations can be repeated in each new training dataset.

RESULTS AND DISCUSSIONS

The obtained optimization results are illustrated for different groups of beams, columns, floors and foundations. They are also represented as numbers. ML optimization results are confirmed with manual design values for all groups of all individual components.

Comparison of graphs area from ML,

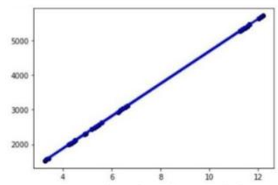

Fig 6 Length and steel cost relation

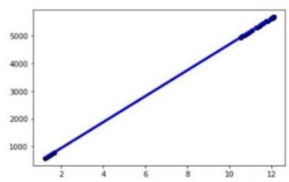

Fig 7 Length and steel cost relation

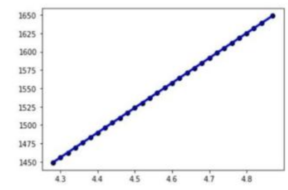

Fig 8 Length and concrete cost relation

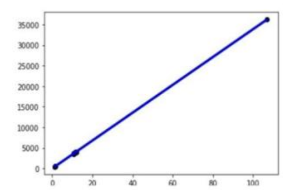

Fig 9 Length and concrete cost relation

- Dotes points are Actual cost, and Line is predicted cost.

Table 1 Comparison between calculated cost and cost obtained using ML model for GF beam Steel.

Case No	ActualCost	Predicted Cost	Diff %
1	5279.597808	5279.597808	-1.364242e-09
2	5321.797080	5321.797080	-7.294148e-10
3	5368.685160	5368.685160	-2.455636e-11
4	5415.573240	5415.573240	6.793925e-10
5	5462.461320	5462.461320	1.385160e09

Table 2 Comparison between calculated cost and cost obtained using ML model for GF Column Steel.

Case No	Actual Cost	Predicted Cost	Diff %
1	5708.62374	5708.62374	-9.094947e-13
2	5673.45768	5673.45768	9.094947e-13
3	5650.01364	5650.01364	-9.094947e-13
4	5626.56960	5626.56960	-9.094947e-13
5	5603.12556	5603.12556	0.000000e+00

Table 3 Comparison between calculated cost and cost obtained using ML model for GF slab Steel.

Case No	Actual Cost	Predicted Cost	Diff %
1	1204.551473	1204.551473	4.769390e-09
2	1254.138167	1254.138167	3.322889e-07
3	1302.374250	1302.374250	-6.481287e-09
4	1269.187825	1269.187825	3.628033e-07
5	1310.092023	1310.092023	-3.086727e-07

Table 4 Comparison between calculated cost and cost obtained using ML model for GF Footing Steel.

Case No	Actual Cost	Predicted Cost	Diff %
1	1871.012448	1872.315397	-1.302949
2	1884.188592	1871.159106	13.029486
3	1897.364736	1886.186059	11.178677
4	1910.540880	1902.735119	7.80561
5	1923.717024	1911.672053	12.044971

Table 5 Comparison between calculated cost and cost obtained using ML model for FF Beam Steel.

Case No	Actual Cost	Predicted Cost	Diff %
1	5279.597808	5279.597808	2.078286e-08
2	5298.353040	5298.353040	2.068464e-08
3	5307.730656	5307.730656	2.063643e-08
4	5321.797080	5321.797080	2.056458e-08
5	5462.461320	5462.461320	1.983517e-08

Table 6 Comparison between calculated cost and cost obtained using ML model for FF Column Steel.

Case No	Actual Cost	Predicted Cost	Diff %
1	3516.6060	3448.239453	68.366547
2	3633.8262	3661.484579	-27.658379
3	3751.0464	3744.714631	6.331769
4	3868.2666	3892.952221	-24.685621
5	3985.4868	4006.185752	-20.698952

Table 7 Comparison between calculated cost and cost obtained using ML model for FF Slab Steel.

Case No	Actual Cost	Predicted Cost	Diff %
1	1440.715337	1440.715337	-7.089579e-08
2	1449.011943	1449.011943	-4.048261e-07
3	1466.376933	1466.376933	-4.064032e-07
4	1485.671367	1485.671367	2.745999e-07
5	1171.172103	1171.172103	-3.551863e-07

Table 8 Comparison between calculated cost and cost obtained using ML model for SF Beam Steel.

Case No	Actual Cost	Predicted Cost	Diff %
1	5279.597808	5279.597808	9.094947e-13
2	5298.353040	5298.353040	0.000000e+00
3	5345.241120	5345.241120	-9.094947e-13
4	5392.129200	5392.129200	0.000000e+00
5	5439.017280	5439.017280	0.000000e+00

Table 9 Comparison between calculated cost and cost obtained using ML model for SF Column Steel.

Case No	Actual Cost	Predicted Cost	Diff %
1	3516.6060	3448.239453	68.366547
2	3633.8262	3661.484579	-27.658379
3	3751.0464	3744.714631	6.331769
4	3868.2666	3892.952221	-24.685621
5	3985.4868	4006.185752	-20.698952

Table 10 Comparison between calculated cost and cost obtained using ML model for SF Slab Steel.

Case No	Actual Cost	Predicted Cost	Diff %
1	771.777333	771.777333	-2.850481e-08
2	777.565663	777.565663	-2.861111e-08
3	789.142323	789.142323	-2.882371e-08
4	796.860097	796.860097	3.770117e-08
5	825.801747	825.801747	3.716957e-08

Table 1 Comparison between calculated cost and cost obtained using ML model for GF Beam Concrete.

Case No	Actual Cost	Predicted Cost	Diff %
1	3812.1856	3834.923179	-22.737579
2	3842.6560	3854.808844	-12.152844
3	3876.5120	3876.904027	-0.392027
4	3910.3680	3898.999211	11.368789
5	3944.2240	3921.094394	23.129606

Table 2 Comparison between calculated cost and cost obtained using ML model for GF slab Concrete.

Case No	Actual Cost	Predicted Cost	Diff %
1	3876.2496	4190.619499	-314.369899
2	4305.6000	4604.210079	-294.610079
3	4740.0000	5013.292634	-273.292634
4	4493.7216	4792.906539	-299.184939
5	4854.7200	5133.669967	-278.949967

Table 3 Comparison between calculated cost and cost obtained using ML model for GF Column Concrete.

Case No	Actual Cost	Predicted Cost	Diff %
1	1648.7872	1648.7872	0.000000e+00
2	1638.6304	1638.6304	2.273737e-13
3	1631.8592	1631.8592	2.273737e-13
4	1625.0880	1625.0880	2.273737e-13
5	1618.3168	1618.3168	0.000000e+00

Table 4 Comparison between calculated cost and cost obtained using ML model for GF Footing Concrete.

Case No	Actual Cost	Predicted Cost	Diff %
1	4020.916215	4020.916215	-6.836215
2	4494.6880	4426.325850	68.362150
3	4657.7664	4599.283136	58.483264
4	4782.1600	4743.183878	38.976122
5	4908.7488	4887.084620	21.664180

Table 5 Comparison between calculated cost and cost obtained using ML model for FF Beam Concrete.

Case No	Actual Cost	Predicted Cost	Diff %
1	3812.1856	3568.315162	243.870438
2	3842.6560	3591.736227	250.919773
3	3876.5120	3617.759632	258.752368
4	3910.3680	3643.783038	266.584962
5	3944.2240	3669.806444	274.417556

Table 6 Comparison between calculated cost and cost obtained using ML model for FF Column Concrete.

Case No	Actual Cost	Predicted Cost	Diff %
1	1015.6800	901.159729	114.520271
2	1177.3056	1156.629074	20.676526
3	1224.7040	1199.572155	25.131845
4	1335.8400	1348.778369	-12.938369
5	1416.3584	1440.765973	-24.407573

Table 7 Comparison between calculated cost and cost obtained using ML model for FF slab Concrete.

Case No	Actual Cost	Predicted Cost	Diff %
1	5499.5136	5036.792286	462.721314
2	5552.6400	5068.297185	484.342815
3	5703.6000	5169.083946	534.516054
4	5856.7680	5266.142747	590.625253
5	2103.8400	2556.675092	-452.835092

Table 8 Comparison between calculated cost and cost obtained using ML model for SF Beam Concrete.

Case No	Actual Cost	Predicted Cost	Diff %
1	3812.1856	3812.1856	-4.547474e-13
2	3825.7280	3825.7280	-4.547474e-13
3	3859.5840	3859.5840	-4.547474e-13
4	3893.4400	3893.4400	0.000000e+00
5	3927.2960	3927.2960	-4.547474e-13

Table 9 Comparison between calculated cost and cost obtained using ML model for SF Column Concrete.

Case No	Actual Cost	Predicted Cost	Diff %
1	1015.6800	901.159729	114.520271
2	1177.3056	1156.629074	20.676526
3	1224.7040	1199.572155	25.131845
4	1335.8400	1348.778369	-12.938369
5	1416.3584	1440.765973	-24.407573

Table 10 Comparison between calculated cost and cost obtained using ML model for SF Slab Concrete.

Case No	Actual Cost	Predicted Cost	Diff %
1	1174.8032	1174.8032	0.0
2	1184.9600	1184.9600	0.0
3	1205.2736	1205.2736	0.0
4	1218.8160	1218.8160	0.0
5	1269.6000	1269.6000	0.0

Comparison of Results

Table 2 Comparison between Manual Calculation and **XGB**

	Manual Calculation	XG Boost Prediction in ML
Cost (Lakh)	29,35,5269	24,57,566
Height in m	11.400	11.150

CONCLUSION

The Following Conclusions can be drawn from this Study.

1. A two-story frame consisting of beams, columns, floors and foundations has been successfully optimized using ML optimization.
2. Optimized two-stage design including code specification IS-456:2000.
3. This study shows that heuristic methods and machine learning optimization tools are effective for optimized design of RC frameworks.
4. The variables used to obtain the optimal design are the effective depth and reinforcement area of beams, columns, slabs and foundations.
5. Results obtained by ML optimization have been verified by comparing with results obtained by manual calculation. The optimization results obtained for the reinforcement region of the element correspond exactly to the values obtained by manual calculation. From this, we can conclude that the design obtained by the proposed method is safe and economical.
6. The cost variation of the frame depending on the type of concrete was studied and found to be the smallest. M20 concrete type deviations are observed. And steel grade is used for Fe415.
7. We have studied the comparison between optimization results and AutoCAD design results. It has been found that the reduction in depth for beams and reinforcement can be up to 25%, compared to more than 50% for columns.
8. Cost comparison is a manual result. We found that we were able to reduce beams by 7.5% and columns by 45%. The optimized result has reduced the overall cost of the frame by 17%.

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