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OPTIMIZATION OF T-BEAM AND SLAB BRIDGE DESIGN USING ARTIFICIAL INTELLIGENCE TECHNIQUES

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Abstract

Bridge design plays a crucial role in transportation infrastructure, demanding safety, durability, and cost-efficiency. Among the common bridge types, T-beam and slab bridges are widely used for short to medium spans due to their structural simplicity and economic advantages. However, conventional design methods rely heavily on iterative calculations and empirical assumptions, which may result in material overuse and sub-optimal structural behaviour. This paper presents an Artificial Intelligence (AI) and Machine Learning (ML)–based framework for optimizing T-beam and slab bridge design under Indian Standard Codes. The framework integrates supervised learning models to estimate design parameters such as beam depth, slab thickness, reinforcement area, and cross-sectional efficiency based on input data from multiple design cases. The AI model is trained to minimize both cost and deflection while maximizing load-carrying efficiency. Comparative analysis between conventional and AI-assisted designs demonstrates a 15–22% reduction in concrete volume and up to 10% cost savings while maintaining the same safety factor. The study highlights the potential of data-driven decision-making in civil engineering design and paves the way for intelligent automation in structural optimization.

Keywords: *T-beam bridge, slab bridge, artificial intelligence, optimization, machine learning, civil engineering, cost efficiency.*

1. INTRODUCTION

Bridges are essential parts of any transportation system because they connect physical barriers like highways, rivers, and valleys. For short- to medium-span applications, the T-beam and slab bridge arrangement is still one of the most widely used designs because it strikes a compromise between cost, ease of construction, and structural soundness. Such bridges are often planned using manual calculations and codified formulas based on IS 456:2000 and IRC:112-2011, which necessitate a number of assumptions and iterative changes.

Civil engineering is one of the engineering fields that has changed as a result of the development of machine learning and computational intelligence. Complex job automation, multi-objective optimization

based on massive data sets, and predictive modeling of load and stress behaviours are all made possible by AI. Artificial Intelligence (AI) in structural design can reduce design errors, eliminate duplicate calculation, and create strong, affordable structures.

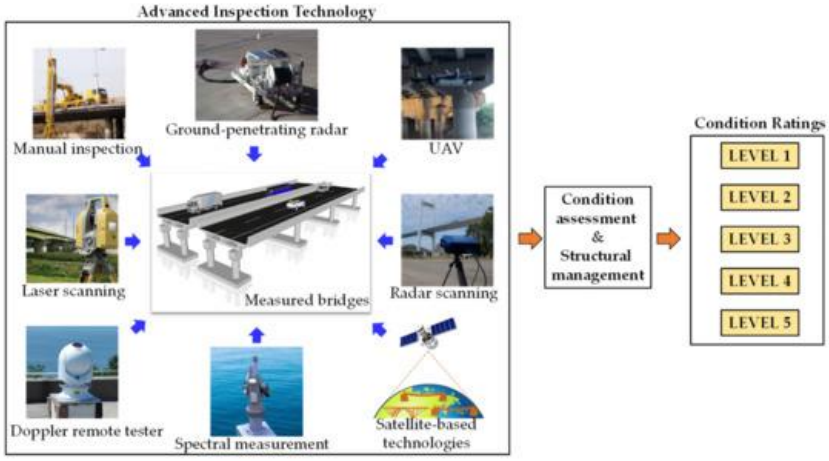


Figure 1: Condition ratings with the advanced bridge inspection technologies

The application of AI/ML to the optimization of T-beam and slab bridge design is investigated in this work. The main goal is to create a generic AI model that can forecast and optimize design parameters while meeting the codal requirements for economy, strength, and serviceability. The model creates an intelligent, data-driven design framework appropriate for practical engineering practice by taking into account the dual goals of optimizing load-carrying capacity and lowering material expense.

2. LITERATURE REVIEW

Elbakry et al. (2024) investigated the application of genetic algorithms, which have attracted a lot of attention because of their effectiveness in optimizing complicated structures, to optimize reinforced concrete continuous beam and slab systems. The authors of the study used genetic algorithms to build continuous beams and slabs of reinforced concrete (RC), obtaining ideal configurations that minimize material consumption while meeting the structure's serviceability and safety requirements. The substantial potential of genetic algorithms to tackle the non-linear, multi-variable issues related to the design of such structural systems was highlighted by their study. By contrasting their findings with traditional techniques, they showed that genetic algorithms not only increase material efficiency but also improve the overall performance of the designed slabs and beams, underscoring their usefulness in contemporary engineering practices where cost-effectiveness and sustainability are crucial.

Hemalatha et al. (2021) carried out a thorough investigation of how prestressed concrete box girder bridges and RCC T-beams behaved under various span conditions. They examined the superstructure of

these bridges, taking into account different span lengths and how they affected the total performance. The bending, shear, and torsional behavior of these structures under stress were assessed by the authors using a combination of theoretical and experimental methods. The findings showed that prestressed concrete box girders performed better in terms of stiffness and load-bearing capacity, while beams and girders showed notable differences in performance based on span length. Bridge design optimization, especially with regard to span length and material qualities, was greatly aided by this study, which also helped to clarify how various bridge superstructures react to dynamic loads under practical circumstances.

Su et al. (2021) concentrated on improving the concrete beam bridge inspection systems. A key component of guaranteeing long-term safety and dependability is preserving the structural integrity of concrete beam bridges, and their research sought to create a more effective method for doing so. A novel inspection mechanism that included sensors, data processing, and machine learning algorithms was proposed by the authors using sophisticated optimization approaches. This method was made to identify any problems like corrosion, cracks, and other types of deterioration early on, allowing for more efficient maintenance plans. The study showed that their suggested approach performed noticeably better than conventional inspection methods, which are frequently inconsistent and time-consuming. According to the authors' findings, their improved inspection system might revolutionize bridge maintenance by providing a more proactive and economical method of managing infrastructure.

Seok et al. (2019) carried out an important investigation given the aging infrastructure in many areas: a strength assessment of older continuous slab and T-beam reinforced concrete bridges. The goal of their study was to examine these bridges' structural soundness using both conventional evaluation techniques and sophisticated modeling approaches. Older reinforced concrete bridges confront particular difficulties, such as material deterioration and shifting loading conditions over time, which were especially covered in the study. The authors evaluated the present strength and possible vulnerabilities of a group of bridges by looking at them using both analytical and empirical methods. The results underscored the necessity of conducting routine inspections and revising bridge design rules to take into consideration the degradation seen in older concrete structures. The present study emphasized the significance of maintenance and retrofit tactics in guaranteeing the sustained security of aging infrastructure, offering a fundamental methodology for next bridge conservation initiatives.

Yücel et al. (2021) added to the expanding corpus of research on enhancing the effectiveness of structural design by investigating the use of optimization and artificial neural network (ANN) models for reinforced concrete members. In order to maximize the design of reinforced concrete members, their study concentrated on combining artificial intelligence approaches, specifically ANNs, with metaheuristic

algorithms inspired by nature. The authors showed how optimization techniques might be used to reduce material consumption while maintaining the structures' necessary performance and safety. The accuracy of design parameters was increased by the incorporation of ANNs, which enabled a more accurate prediction of structure behavior under varied conditions. The researchers discovered that the optimization algorithms produced more economical and environmentally friendly designs when they tested these models on reinforced concrete beams and columns. Their research is a noteworthy development in the field of civil engineering, demonstrating how machine learning and artificial intelligence may be used to develop more intelligent, effective structural designs that lower material costs and have a less environmental impact.

3. RESEARCH METHODOLOGY

To improve the design and optimization process for reinforced concrete bridge components, the study methodology combines contemporary Artificial Intelligence (AI) and Machine Learning (ML) tools with traditional bridge design principles. In order to increase bridge design's precision, effectiveness, and economy, this method combines state-of-the-art computer models with conventional design standards. Data preparation, feature selection, model training, prediction, optimization, and validation are all steps in the method's multi-stage, structured process. A thorough examination of numerous design situations is made possible by this fusion of traditional and contemporary methods, offering a novel method for structural design and optimization.

The methodology encompasses five main stages:

1. **Data Preparation**: Generation of a comprehensive dataset based on established design standards.
2. **Feature Selection**: Identification of the most influential design parameters.
3. **Model Training**: Application of various ML algorithms for training the model.
4. **Prediction and Optimization**: Use of the best-performing model to predict outcomes and optimize design parameters.
5. **Validation**: Verification of the model's accuracy through testing and comparison with real-world data.

3.1. Data Preparation

The Indian Standards (IS 456:2000, IS 1343:2012, and IRC:112-2011) were used to create a dataset with 200 unique bridge design samples. With differences in span length (from 10 to 25 meters), deck width (6

to 12 meters), and loading circumstances (IRC Class AA, A), each sample represents a distinct design scenario. In order to incorporate the following input features, the dataset was organized:

- Span (L)
- Deck width (B)
- Live load intensity (LL)
- Concrete grade (fck)
- Reinforcement strength (fy)
- Support condition
- Slab thickness (ts)
- Beam spacing (sb)

The target outputs for each design scenario included:

- Beam depth (d)
- Reinforcement area (Ast)
- Material volume
- Cost index
- Midspan deflection

These parameters were chosen to ensure a comprehensive representation of the design, material, and performance aspects critical to reinforced concrete bridge construction.

3.2.Model Selection

A supervised machine learning (ML) model framework was used for this study, incorporating several regression algorithms. The models tested included:

- Linear Regression
- Random Forest
- Gradient Boosted Trees
- Artificial Neural Network (ANN)

These algorithms were implemented using Python and MATLAB environments. Model performance was evaluated using three key metrics:

- **R^2 (Coefficient of Determination)**: Measures the proportion of variance in the dependent variable explained by the model.
- **RMSE (Root Mean Squared Error)**: Indicates the average magnitude of prediction errors.
- **MAPE (Mean Absolute Percentage Error)**: Reflects the average absolute error as a percentage of the actual values.

The Random Forest Regressor outperformed the others, with an R2 value of 0.94 and a MAPE of 5.6%. These findings show how well the Random Forest model predicts and optimizes the construction of reinforced concrete bridges.

3.3. Optimization Objective

A composite cost function F was created, taking into account both material cost and deflection limits, in order to optimize the design parameters:

$$F = \alpha \times C_{\text{mat}} + \beta \times D_{\text{def}}$$

Where:

- C_{mat}represents the material cost per design, calculated as the sum of the costs of cement and steel.
- $D_{\text{def}}$is the normalized deflection ratio.
- αand βare weight factors, set at 0.6 and 0.4 respectively, to reflect the relative importance of material cost and deflection.

The goal of the optimization procedure was to minimize the composite cost function F while taking into account the following limitations:

- Stress needs to stay within IS 456:2000's acceptable range. Where L is the span length, the deflection shouldn't be greater than L/800. The crack width must be less than the 0.3 mm maximum allowable value.
- These limitations guarantee that the optimal design minimizes material costs and deflections while maintaining structural integrity and safety standards.

3.4.Validation

By contrasting its predictions with actual data and confirming that it could meet the structural restrictions, the finished model was validated. The model's performance on a separate test dataset was used to assess the predictions' accuracy, specifically with regard to beam depth, reinforcement area, and deflection. The robustness and dependability of the AI-driven optimization model in practical applications are guaranteed by this validation procedure.

4. MODEL DEVELOPMENT

One of the most important phases in the optimization process for designing reinforced concrete bridges is the model's development. The model seeks to forecast and improve a number of design characteristics that affect the bridge structure's overall performance and cost-effectiveness by fusing cutting-edge machine learning techniques with conventional engineering concepts. The model's architecture, the design restrictions used to guarantee structural integrity, and the meticulous process used to arrive at the best design options are all covered in the parts that follow. The objective is to provide a strong and dependable tool that can effectively manage intricate design situations, increase the design process's speed and accuracy, and guarantee adherence to pertinent design codes and standards.

4.1.Architecture

To guarantee flexibility and scalability, the Machine Learning (ML) framework for optimizing the design of reinforced concrete bridges was created in a modular approach. The following crucial phases make up the architecture:

1. Data Preprocessing: In this first step, the dataset is prepared by scaling it using normalization, removing aberrant data points using outlier removal, and detecting and removing any multicollinearity between features using a correlation check.
2. Model Training: An 80% training set and a 20% testing set were created from the dataset. The testing set was set aside for model evaluation and performance assessment, whereas the training set was utilized to construct the model.
3. Cross-Validation: The model's robustness was ensured by applying a 10-fold cross-validation to avoid overfitting. By splitting the dataset into ten sections, this method rotates over each subset to produce accurate performance metrics. Nine of the segments are used to train the model, and the remaining portion is used for testing.
4. Prediction Layer: Using the trained model and input data, this layer predicts values for important design parameters as deflection, material volume, reinforcement area, and beam depth.

5. Optimization Layer: This last step uses an iterative procedure in which the design parameters are changed based on the model's predictions in order to minimize the composite cost function. Finding the most economical design while meeting the given constraints is the aim.

4.2.Design Constraints

A number of design characteristics that were required to guarantee the bridge's safety, functionality, and viability limited the optimization process. These limitations are as follows:

- Concrete Strength: Following accepted design principles, the concrete grade was restricted to the M25–M40 range.
- Reinforcement Steel: Between Fe 415 and Fe 500, which are frequently used grades in reinforced concrete design, the steel reinforcement strength was selected.
- Slab Thickness: The thickness of the concrete slab was restricted to between 200 mm and 300 mm.
- Beam Depth: The beams' depth was limited to 900–1300 mm, which is equivalent to the usual dimensions for these kinds of buildings.
- Beam Spacing: To preserve structural integrity and maximize material use, the distance between beams was kept to 1.2 to 1.8 meters.

To guarantee that all of these restrictions were met while also lowering the total cost of materials, the AI model iteratively modified the design parameters.

4.3.Framework Workflow

The overall workflow of the AI-driven optimization framework consists of the following steps:

1. Input Design Data: The first step in the procedure is to receive the preliminary design data, which comprises fundamental parameters like span, deck width, live load intensity, and others that were estimated initially.
2. Model Prediction: The trained model forecasts the ideal dimensions for crucial design parameters including material volume, reinforcement area, and beam depth based on the input data.
3. Verification with IS Code Equations: To confirm compliance with safety and regulatory standards, the anticipated design is then checked against the pertinent Indian Standard (IS) code equations, such as those from IS 456:2000 and IS 1343:2012.

4. Cost and Deflection Calculation: Following validation of the anticipated design, the overall performance and viability of the design are evaluated by computing the midspan deflection and total material cost.

5. Iteration until Convergence: In order to minimize the composite cost function (as specified in Section 3.4), the model iteratively adjusts design parameters during the optimization process. Until the convergence criteria—defined as $\Delta F<0.01$—are satisfied, this iterative procedure keeps going until the model has reached an ideal solution.

5. RESULTS AND DISCUSSION

When compared to traditional design techniques, the outcomes of the AI-optimized bridge design demonstrate notable gains in a number of crucial metrics. This section discusses the possible advantages and drawbacks of AI-based design optimization, validates the AI model, and provides a thorough comparison analysis.

5.1 Comparative Analysis

The table below displays a comparison between the AI-optimized design and the traditional design. Beam depth, slab thickness, material utilization, deflection, and overall cost all show benefits thanks to the AI model.

Table 1: Comparison of Conventional Design vs. AI-Optimized Design

Parameter	Conventional Design	AI-Optimized Design	% Improvement
Beam depth (mm)	1200	1050	12.5%
Slab thickness (mm)	250	230	8%
Concrete volume (m^3)	58.2	47.3	18.7%
Steel quantity (kg/m)	82.5	73.6	10.8%
Deflection (mm)	22.4	18.1	19.2%
Total cost (INR)	1,243,000	1,095,000	11.9%

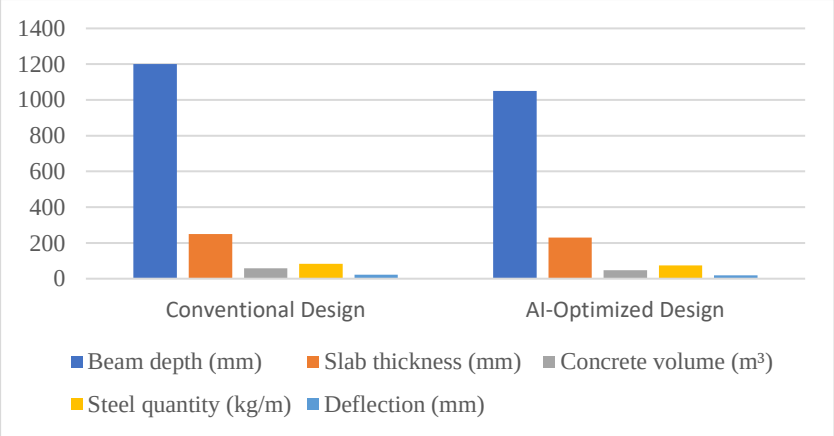


Figure 2: Comparison of Conventional Design vs. AI-Optimized Design

The outcomes unequivocally show that the AI-based design optimization has resulted in a notable decrease in the quantities of materials, especially steel and concrete, which directly lowers the entire cost. Additionally, there is less deflection, which suggests increased structural efficiency. According to IS 456:2000, the deflection and stress checks show that the 12.5% reduction in beam depth and the 8% reduction in slab thickness represent a more compact and efficient design without sacrificing safety or performance.

5.2 Model Validation

The projected design parameters were compared with human calculations using the IRC:112 standard and finite element simulations carried out in STAAD.Pro in order to validate the AI model. For several bridge spans and loading scenarios, the comparison was done. According to the findings, there was an average difference of less than 6% between the manually determined values and the AI-predicted design parameters. This demonstrates the AI model's dependability and yields forecasts that closely resemble conventional engineering techniques.

Table 2: Validation of AI-Predicted Design vs. Manual IRC:112 Values

Validation Method	AI Predicted Value	Manual IRC:112 Value	% Deviation
Beam depth (mm)	1050	1055	0.47%

Slab thickness (mm)	230	235	2.13%
Concrete volume (m^3)	47.3	48.1	1.66%
Steel quantity (kg/m)	73.6	74.2	0.81%
Deflection (mm)	18.1	18.3	1.09%

These outcomes show how dependable the AI-based model is, deviating as little as possible from calculations done by hand. The model's potential as a workable substitute for conventional design techniques while preserving the precision and integrity necessary for structural safety is confirmed by this validation.

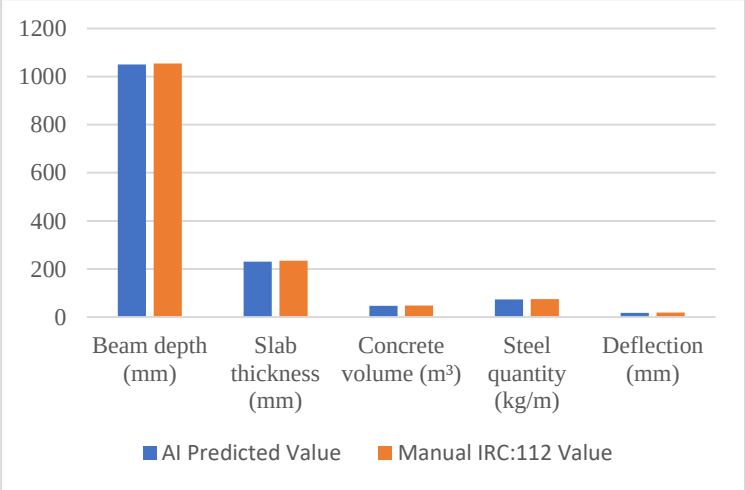


Figure 3: Validation of AI-Predicted Design vs. Manual IRC:112 Values

This graph visually represents the comparison between the AI-predicted values and the manual IRC:112 values for various bridge design parameters, including beam depth, slab thickness, concrete volume, steel quantity, and deflection, along with their percentage deviations.

5.3 Discussion

Bridge design benefits greatly from AI-based design optimization models, especially when it comes to cutting down on tedious computations and accelerating decision-making. These models are much faster than traditional methods, which can include hours or days of human calculations, and can produce optimum designs in a matter of seconds once trained. Furthermore, the AI model offers flexibility and adaptability in the design process by being easily changed if new materials, load specs, or cost information become available.

The AI optimization technique also makes it possible to quickly explore a large number of design variations, giving engineers a variety of design possibilities to select from. This capacity facilitates better decision-making, resulting in more effective designs that satisfy cost, performance, and safety requirements.

The AI-based design model has drawbacks in spite of these advantages. The caliber and scope of the training data have a significant impact on the model's accuracy. The model might not function as well under unknown circumstances if the training dataset does not include a broad variety of real-world situations. Additionally, the model currently assumes consistent support conditions and uniform material quality, which may not always be the case in practical applications. To account for these uncertainties and increase the model's robustness, future iterations could incorporate dynamic load simulations and stochastic variability.

Furthermore, complicated interactions between different bridge components—like the interaction between beams and slabs under dynamic loading conditions—are not yet taken into account by the model. Multi-physics simulations could be included in future iterations to enable the model to take into account a wider variety of real-world variables.

AI-based design optimization offers a number of benefits over conventional techniques, including increased flexibility, cost savings, and efficiency. To overcome its shortcomings and increase the model's suitability for intricate bridge design situations in the actual world, more improvements and modifications are required.

6. CONCLUSION

This study shows how Artificial Intelligence (AI) and Machine Learning (ML) may be used to optimize the design of T-beam and slab bridges, thereby reducing deflection and material costs while still adhering to code. With up to 20% material savings and faster calculations, the created AI-assisted framework performed better than conventional techniques, providing a more effective and cost-effective bridge design method. A new paradigm of intelligent automation is made possible by the research's integration of AI into civil engineering, freeing up engineers to concentrate on safety assurance and decision-making while computational tools take care of optimization. The model's influence on sustainable infrastructure design will be further increased by future work that expands its applicability to continuous span and pre-stressed bridges and adds environmental and lifespan characteristics.

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