

**ANN-BASED APPROACH FOR SELECTION OF  
OPTIMUM FLOOR SYSTEM OF MULTI-STORIED  
BUILDINGS IN THE PRELIMINARY DESIGN STAGE**

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## **DECLARATION**

I declare that this is my own work, and this thesis does not incorporate without acknowledgement any material previously submitted for a degree or diploma in any other University or Institute of higher learning and to the best of my knowledge and belief it does not contain any material previously published or written by another person except where the acknowledgement is made in the text. I retain the right to use this content in whole or part in future works (such as articles or books).

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Date: 26-08-2025

The above candidate has carried out research for the Masters thesis/dissertation under my supervision. I confirm that the declaration made above by the student is true and correct.

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## ABSTRACT

Eco-friendly and climate-resilient building concepts are globally emerging with increasing Greenhouse Gas (GHG) emissions from the building sector. Addressing the embodied carbon of floor systems becomes essential as these contribute more than 50% of the embodied energy of the building footprint. Whereas, in the Preliminary Design Stage (PDS), striving for the best alternative satisfying performance, economic and environmental criteria is challenging within a limited time while decision-making is generally from the expertise's design sense and intuition. Engineers in design firms have been encountering these recursive design processes over the years; however, the rate of reutilization of the previous design information and experience is very rare. Machine Learning (ML) techniques can offer smart decision-making tools in the PDS. Nevertheless, only a few addressed the optimization in the PDS while none of the studies comprehensively addressed the optimum floor system considering all three criteria simultaneously. This study utilized a human brain mimicking algorithm, Artificial Neural Network (ANN) in the optimization of reinforced-concrete floor systems of a multi-storied building in the PDS encapsulating the performance, economic and environmental considerations with the aid of data collection from the constructed buildings in Sri Lanka. The eight distinct models are proposed to predict each quantity in both Beam-Slab System (BSS) and Flat-Slab System (FSS). The proposed models in the BSS database are recorded predictions with  $R^2$  values of above 0.8 demonstrating reasonable performance in the heterogeneous real-world data while the models in the FSS database show superior performance which yields  $R^2$  values greater than 0.95 with synthetic data. Also, the predictions from all the models fall below a 30% error margin and the models in the FSS database demonstrated the higher performance with significantly lower error margins of 10 to 20%. Further, a conducted comparative analysis with the range of alternative ML models demonstrates the performance and capabilities of human-brain-inspired ANN under heterogeneous and high-dimensional data with inherently qualitative in nature. SHAP explanations demonstrated the relative contribution of each feature in the quantity predictions which in turn streamlined the confidence in the end-users. The trained ANN model is finally transformed into a design tool to facilitate the engineers to predict quantities that offer a platform to select the optimized floor system in the PDS.

**Keywords:** Optimization, Reinforced-concrete floor systems, ANN, SHAP explanations

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## LIST OF ABBREVIATIONS

| Abbreviation    | Description                                        |
|-----------------|----------------------------------------------------|
| AdaDelta        | Adaptive Delta                                     |
| AdaGrad         | Adaptive Gradient                                  |
| Adam            | Adaptive Moment Estimation                         |
| AI              | Artificial Intelligence                            |
| ANN             | Artificial Neural Network                          |
| API             | Application Programming Interface                  |
| BSS             | Beam-Slab System                                   |
| CART            | Classification And Regression Trees                |
| CO <sub>2</sub> | Emissions CO <sub>2</sub> Global Warming Potential |
| CPU             | Central Processing Unit                            |
| CSS             | Combined Slab System                               |
| CUI             | Concrete Usage Index                               |
| CV              | Cross-Validation                                   |
| DT              | Decision Tree                                      |
| ECE             | Embodied Carbon Energy                             |
| ELU             | Exponential Linear Unit                            |
| FSS             | Flat-Slab System                                   |
| FTRL            | Follow The Regularized Leader                      |
| GELU            | Gaussian Error Linear Unit                         |
| GHG             | Green House Gas                                    |
| GL              | Grid Length                                        |
| GPU             | Graphics Processing Unit                           |
| GWP             | Global Warming Potential                           |
| ICE             | Inventory of Carbon and Energy                     |
| IQR             | Inter Quartile Range                               |
| MAD             | Mean Absolute Deviation                            |
| MAE             | Mean Absolute Error                                |
| ML              | Machine Learning                                   |
| MSE             | Mean Square Error                                  |

|         |                                                        |
|---------|--------------------------------------------------------|
| Nadam   | Nesterov-accelerated Adaptive Moment Estimation        |
| NLP     | Nonlinear Programming                                  |
| NRMSE   | Normalized Root Mean Squared Error                     |
| PDS     | Preliminary Design Stage                               |
| ReLU    | Rectified Linear Unit                                  |
| R/F     | Reinforcement                                          |
| RF      | Random Forest                                          |
| RMSProp | Root Mean Square Propagation                           |
| ROC AUC | Receiver Operating Characteristic Area Under the Curve |
| RUI     | Reinforcement Usage Index                              |
| SELU    | Scaled Exponential Linear Unit                         |
| SGD     | Stochastic Gradient Descent                            |
| SHAP    | Shapley Additive Explanations                          |
| SLS     | Serviceability Limit State                             |
| VC      | Volume of Concrete                                     |
| VRF     | Volume of Reinforcement                                |
| ULS     | Ultimate Limit State                                   |
| XAI     | Explainable Artificial Intelligence                    |