

# AI driven Foundation and Material Recommendation for Sustainable Construction

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**Abstract—** In the realm of sustainable architecture and civil engineering, optimizing foundational and material components is pivotal for achieving structural stability and environmental efficiency. An innovative AI-driven parametric design tool tailored to address these crucial aspects by leveraging real-time environmental data and material properties. The tool aims to enhance decision-making, reduce carbon footprint, and ensure cost-effective construction practices. The Foundation Model plays a vital role by utilizing comprehensive soil data, including specific gravity, and moisture content, collected from multiple borehole samples. Processed through SQLite, this model provides precise foundation type recommendations, ensuring stability and cost efficiency under diverse geological conditions. The Material Model evaluates essential material properties such as thermal conductivity, water absorption, permeability, and durability. It emphasizes selecting sustainable building materials tailored to different climate zones, promoting energy efficiency and reducing environmental impact. By focusing on these two core components, the project demonstrates the potential of AI in transforming traditional construction methodologies. This offers a forward-thinking approach to material and foundation optimization, contributing to the advancement of sustainable architecture. Through data-driven insights and automation, it paves the way for more resilient and eco-friendly building designs

**Keywords—** Foundation, Material Selection, AI model, Sustainability Introduction

## I. INTRODUCTION

The construction industry faces the twin challenge of reducing carbon emissions while ensuring buildings remain safe, durable, and economically feasible [6]. This is complicated by the continued use of traditional methods that often neglect site-specific geotechnical conditions, material performance, and long-term environmental impact. Buildings significantly contribute to global energy use and emissions through systems like heating and cooling, all shaped by early design choices [1]. Urbanization, climate change, and limited

resources necessitate a shift toward energy-efficient, location-sensitive design strategies. Conventional approaches often fail to account for the complex interactions between soil behavior, material properties, occupant comfort, and sustainability standards. In foundation engineering specifically, generic design practices frequently lead to either overdesign or unsafe outcomes by ignoring detailed soil characteristics such as specific gravity, moisture content, and bearing capacity [7] [8]. To address these limitations, this study introduces an AI-powered parametric framework that incorporates detailed site-specific soil data alongside material performance metrics. The model aims to optimize foundation type selection and material use, enhancing both structural precision and environmental performance [10]. This data-driven approach promotes smarter, sustainable construction tailored to diverse regional conditions, advancing the shift toward intelligent, eco-friendly building technologies.

## II. METHODOLOGY

The proposed design tool consists of two interdependent and synergistic models:

### A. Foundation model

A Foundation Model and a Material Model, which are driven by a SQL database and a Random Forest Regression Classifier, a powerful machine learning algorithm known for its capability to handle complex, nonlinear datasets. For the Foundation Model, essential soil parameters such as specific gravity, bulk density, and moisture content are meticulously collected from a total of 32 borehole samples taken at varying depths, reaching up to 20 meters, across six geographically diverse construction sites. These geotechnical properties are then processed using Python based routines, which interact directly with an SQL database backend dedicated to the Foundation Model for data storage, management, and

calculation [12] [13]. This approach ensures that the SQL database is used specifically for developing the Foundation Model and not for the RandomForest Regression Classifier, which is trained separately. This setup allows for efficient extraction, storage, and preprocessing of large datasets, enabling smooth and organized model development. Simultaneously, structural load estimations are conducted, where dead loads are calculated by analyzing the self-weight of individual structural components, and live loads are assessed by considering dynamic influences introduced by occupants, furniture, and movable objects [10]. The classification of both dead load and live load strictly adheres to the standards and guidelines provided in IS 875, ensuring compliance with established engineering practices. These inputs, combining both geotechnical and structural factors, are used to train the RandomForest Regression Classifier, which is tasked with predicting the most appropriate foundation type whether it be shallow, deep, raft, or mat based on the specific characteristics of each site [11]. To further enhance the model's performance and prevent issues such as overfitting, cross-validation techniques and hyperparameter tuning are applied during training. This ensures that the model maintains a high degree of predictive accuracy and can reliably generalize its recommendations across a variety of soil and loading conditions.

### B. Material Model

The Material Model focuses on material selection for building components such as walls, windows, and doors. It uses a similar AI approach, where environmental data namely temperature and humidity are integrated with material-specific properties like thermal conductivity, durability, and insulation. Trusted data sources provide baseline information on these material properties, which are then used to assign a performance score [6][7]. The RandomForest Regression Classifier is again utilized to process these inputs. In this case, the classifier learns the relationship between the environmental conditions and the performance metrics of each material. By assigning score values that reflect thermal efficiency, durability, and sustainability, the system objectively ranks materials and outputs top recommendations tailored to the local climate[2]. This scoring methodology ensures that the decision-making process is driven by performance criteria rather than merely cost or availability, aligning the material choices with both energy-efficiency and long-term durability goals.

## III. FOUNDATION MODEL

### Data Collection

The Foundation Model is built on a robust set of geotechnical data collected from Engineers Diagnostic Center Pvt. Ltd. in Ernakulam. Measurements from 32 borehole tests across diverse urban sites, including Aluva, Vaduthala, Palarivattom Bypass, Kakkanad Info Park, Eroor, and Brahmapuram, provide a representative dataset of soil properties. Key parameters such as specific gravity, bulk density, and moisture content are measured at multiple depths up to 20 meters. This data forms the basis for load analyses and predictive modeling. All data is securely stored in an SQLite database for efficient access and seamless integration into the computational workflow.

The Material Model relies on a curated dataset to guide material selection. Climate data, including temperature, wind speed, and cloud coverage, is considered based on user-provided geographic coordinates. Thermal performance attributes of materials are sourced from peer reviewed journals, technical datasheets, and environmental databases [3][4]. Key parameters include heat transfer coefficient, thermal resistance, normalized thermal mass, and absorptance. This structured dataset, covering 25 materials for walls, windows, and doors, supports climate-responsive and energy-efficient material selection. Together, these data collection efforts enhance the reliability and effectiveness of the overall design tool.

### Load Calculation And Model Training

The model predicts the optimal foundation type by processing user inputs, including number of floors, floor area, and building type. Load calculations are performed as per IS 875 standards. Dead load and live load are computed using material properties, geometry, and occupancy factors. Combined with soil properties such as specific gravity, bulk density, and moisture content, these inputs are stored in an SQLite database and used within the Foundation Model [9]. The model analyzes structural and geotechnical factors to recommend the most suitable foundation, selecting among shallow, deep, raft, or mat options. Simultaneously, the Material Model supports material selection using climate data including temperature, wind speed, and cloud coverage from user-provided coordinates. Material attributes such as heat transfer coefficient, thermal resistance, normalized thermal mass, and absorptance are sourced from peer reviewed journals and technical datasheets. A RandomForest Regression model, trained on data for twenty five wall, window, and door materials, ranks materials to optimize energy efficiency and climate performance. These processes ensure reliable and effective design recommendations.

```
te('/', 'foundation', methods=['GET', 'POST'])
def foundation():
    soil_data = query.filter_by().all()
    request.method == 'POST':
        location = request.form['location']
        num_stories = int(request.form['story'])
        building_type = request.form['type']
        floor_area = int(request.form['area'])

    if location == 'Other':
        bearing_capacity = request.form['bearing']
    else:
        # Retrieve soil properties
        soil = soil_data.query.filter_by(location=location)
        bearing_capacity = soil[0].bearing_capacity

    # Calculate loads
    dead_load, live_load, total_load = calculate_loads(floor_area, num_stories, building_type)

    foundation = found_data.query.filter_by(usage=building_type)
    # Find suitable foundations
    primary_foundation = None
    detailed_reason = None
    other_options = []

    for foundation in foundation:
        if (foundation.bearing_capacity_l <= bearing_capacity <= foundation.bearing_capacity_h):
```

Fig. 1. Sample of Code for Foundation Model.

### Implementation And Output

The Foundation Model quickly processes new soil data inputs, running through the established pipeline from data extraction through the SQLite database, load calculations, and AI model inference to output a clear recommendation on the optimal foundation type [2][12]. The integration of AI in

this process not only reduces the time taken to make these critical decisions but also minimizes human error, thereby enhancing the reliability of the design process. The result is a tailored, site-specific foundation design recommendation that meets rigorous engineering standards while also accounting for cost efficiency and risk mitigation.

#### IV. MATERIAL MODEL

##### A. Data Collection

The Material Model specifically focuses on the selection of high-performance construction materials for walls, windows, and doors by thoroughly evaluating both intrinsic properties and environmental factors. Material data, including key attributes such as thermal conductivity, durability, and insulation properties, are sourced from a diverse range of reputable journal articles, trusted industry databases, and material specifications from established suppliers [3][4][5]. The model's material selection process encompasses a broad spectrum of materials for various construction components: for roofing, materials like fiber cement, clay tiling, and metal roofing are considered based on their thermal and durability properties; flooring alternatives include options such as clay tiles, glass tiles, and terrazzo, each evaluated for their longevity and environmental impact; window materials span from traditional aluminum and UPVC to more modern and sustainable choices like carbon fiber reinforced polymer; and wall systems incorporate both conventional options, such as rammed earth, and innovative materials like hempcrete and laterite stone, which offer environmentally friendly benefits [3][7]. Table 1 represents the collected material data used for training the Material Model, ensuring that its recommendations are grounded in a comprehensive and reliable dataset. This selection process guarantees that the most appropriate and efficient materials are chosen, tailored to the specific needs of the project and local conditions.

Table 1. Sample of Dataset for wall Materials.

S l . N o	Material	U_ mi n	U_ ma x	R_ mi n	R_ ma x	TM_ mi n	TM_ ma x	A_ mi n	A_ ma x
1	Bamboo	0.17	0.26	3.8	3.9	450	600	0.6	0.75
2	Rammed Earth	1.1	2.3	0.43	0.91	1400	1800	0.65	0.85
3	Baked Brick	1.1	1.8	0.56	0.91	1300	1700	0.70	0.85
4	Cement Block	1.1	1.5	0.67	0.91	1000	1500	0.70	0.85
5	Laterite Block	1.4	2	0.5	0.71	1500	2000	0.65	0.80

##### B. Environmental Inputs and Scoring Process

Recognizing that the performance characteristics of construction materials can vary significantly when exposed to different environmental conditions, the Material Model has been meticulously designed to integrate external climate

related data, particularly temperature and humidity. This integration enables the system to perform highly accurate evaluations by assessing how various materials behave and endure under specific local climatic conditions. By doing so, the system ensures that material recommendations are not generalized or based solely on traditional performance metrics but are instead tailored to the unique environmental context of each construction site [6][7]. This approach makes the model particularly effective for ensuring that materials perform optimally, accounting for factors such as local temperature fluctuations, seasonal humidity, and other climate related variables. The Random Forest Regression Classifier is leveraged as the central predictive mechanism, focused on analyzing and correlating material performance metrics with key environmental variables [2][9]. During the model's training phase, it processes a rich set of historical and experimental data to learn the intricate relationships between the intrinsic properties of each material such as thermal conductivity, durability under stress, and insulation capabilities and their effectiveness when subjected to varying combinations of temperature and humidity. A systematic scoring method is then developed, in which each material is assigned a comprehensive performance score based on multiple factors like thermal efficiency, durability, and insulation performance. These scores are calculated using sophisticated, data driven algorithms, with Equation 1 serving as the basis for the computation of these scores. This ensures that comparisons between materials remain objective, transparent, and free from subjective biases [1]. As a result, the selection process is driven entirely by scientifically derived performance criteria, allowing for highly informed decisions based on material suitability, rather than being influenced by external factors such as cost, popularity, or market availability. This method ensures that the selected materials not only meet technical specifications but are also best suited to the environmental challenges of the project.

*U* - Heat Transfer Coefficient, *R* - Thermal Resistance

*TM* - Normalized Thermal Mass, *A* - Absorptance

$$\text{Score} = w_1 \times U_1 + w_2 \times R + w_3 \times TM + w_4 \times (1 + |0.65 - A|) \quad (1)$$

##### C. Model Training, Validation and Implementation

The training process for the Material Model employs a Random Forest Regression model to validate material performance scores by comparing them against historical data and benchmarks for material efficiency in regions with similar climatic conditions. This ensures that the system's recommendations reflect real-world material behavior under varying environmental stresses. An SQL database is used to store critical material performance data and environmental variables, allowing seamless retrieval and real-time calculations during model operation. This database holds pre-processed material properties and supports the integration of new, updated data to maintain the model's adaptability across diverse scenarios. During operation, the model accesses current environmental inputs, such as temperature and humidity, from the database and dynamically updates material performance scores through the Random Forest Regression model. This real-time analysis ensures that

material recommendations remain aligned with prevailing local conditions [3][9][12]. The system then outputs a ranked list of materials for walls, windows, and doors, tailored to the environmental characteristics of each project site. This ranking enables designers and engineers to make informed decisions based on technical performance metrics, promoting sustainable design practices. By selecting materials optimized for energy efficiency, durability, and resilience, the tool helps reduce a building's environmental impact while enhancing structural longevity [3][4]. Ultimately, the system supports sustainable, cost-effective construction by ensuring that selected materials perform optimally in response to environmental challenges and help lower long-term maintenance and energy costs.

## V. RESULT AND DISCUSSION

Both the Foundation and Material Models demonstrate significant potential in advancing construction design optimization through data-driven methodologies. The Foundation Model leverages a robust SQL database to integrate accurate load calculations with detailed geotechnical data, enabling the generation of highly precise, site-specific foundation recommendations. By incorporating essential soil parameters such as specific gravity, moisture content, and bulk density collected from comprehensive borehole sampling, the model ensures that its outputs are not only technically sound but also finely tuned to the unique characteristics of each site. This capability to predict the most suitable foundation type, whether shallow, deep, raft, or mat, offers considerable benefits by streamlining the structural design process, minimizing material wastage, and reducing overall project costs. Moreover, this approach reduces the reliance on conventional trial and error design iterations, thereby optimizing material usage and enhancing efficiency in both design and construction phases.

In parallel, the Material Model employs a Random Forest Regression model to objectively score and rank construction materials based on key performance factors, including thermal efficiency, durability, and insulation properties. The model incorporates climate-responsive data such as temperature and humidity, ensuring that material recommendations are specifically tailored to local environmental conditions. By systematically analyzing and ranking materials for walls, windows, and doors, the model provides a transparent and scientifically grounded mechanism for material selection. This ensures that the resulting design choices not only meet technical and regulatory standards but also align with broader sustainability objectives, promoting energy efficiency and enhancing the long-term resilience of the built environment.

Together, this integrated dual-model framework effectively reduces uncertainties in construction design and fosters the adoption of environmentally conscious practices. It empowers designers and engineers to make informed decisions that balance structural integrity, material efficiency, and ecological considerations. The discussion further highlights that while both models currently perform robustly within their tested parameters, there remains considerable scope for further enhancement [2][12]. Expanding the framework to incorporate additional

environmental variables such as wind exposure, solar radiation, and broader climate patterns could further improve predictive accuracy and increase the practical utility of the models across an even wider range of construction scenarios and geographic contexts

## VI. CONCLUSION

This paper presents a comprehensive parametric design tool that seamlessly integrates advanced computational methods with real-time environmental and material data, offering a refined approach to optimizing foundation and material selection in civil engineering projects. By leveraging a Random Forest Regression Classifier and SQL database for the Foundation and Material Models, the tool generates highly accurate, site-specific design recommendations that improve structural integrity, enhance cost efficiency, and support long-term sustainability goals. The careful integration of geotechnical data, such as soil parameters, with environmental data, like temperature and humidity, represents a significant advancement in the field of computational civil engineering. This innovative approach paves the way for smarter, more adaptive construction practices that respond to the unique characteristics of each site and environmental condition. Moving forward, future work will focus on expanding the dataset to cover a wider range of geographic areas, integrating additional environmental variables such as wind exposure and solar radiation and developing a more intuitive, user-friendly interface. These planned enhancements will not only broaden the model's applicability across diverse project sites but will also improve its practical utility, ultimately helping to create more resilient, energy-efficient, and eco-friendly built environments.

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