Journal of Engineering and Technology

ISSN 2180-3811 eISSN 2289-814X https://jet.utem.edu.my/jet/index

DOI: https://doi.org/10.54554/jet.2025.16.2.016

A COMPARATIVE ANALYSIS OF FINE TREE REGRESSION AND ANFIS FOR PREDICTING CARBON FOOTPRINTS IN RESIDENTIAL CONSTRUCTION

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Article history:
Received Date: 26 March 2025
Revised Date: 7 August 2025
Accepted Date: 1 September 2025

Keywords:

Abstract— The construction industry is a major contributor to global carbon emissions, necessitating accurate predictive models for sustainable development. This study compares the performance of fine tree regression (Rtree) and adaptive neuro-fuzzy inference system (ANFIS) in predicting carbon footprints across four stages of residential construction: production, transportation, operational, and destruction. A dataset of 2000 observations was used,

Carbon Footprint Prediction, Life Cycle Assessment, Adaptive Neuro-Fuzzy Inference System, Fine Tree Regression, Sustainable Residential Development	with an 80 to 20 split for training and testing. The models were evaluated using root mean square error (RMSE) and mean absolute percentage error (MAPE). Results indicate that ANFIS outperforms Rtree in all stages. ANFIS achieved an RMSE of 0.5142 at the production stage compared to 0.5317 for Rtree. ANFIS obtained an RMSE of 447.07 in the transportation stage, while Rtree recorded 492.23. The operational stage showed an RMSE of 1179.3 for ANFIS versus 1386.5 for Rtree. At the destruction stage, ANFIS demonstrated superior accuracy with an RMSE of 0.0610 compared to 0.0631. The findings suggest that ANFIS provides more precise predictions and is a reliable model for estimating carbon footprints in residential construction. This study contributes to sustainable construction by offering an efficient tool for reducing environmental impact.

I. Introduction

The construction industry is one of the largest contributors to global greenhouse gas emissions, making it a significant factor in climate change. According to Alam Bhuiyan, et al. [1], construction activities accounted for approximately 39% of global final energy consumption and 37% of energy-related carbon dioxide emissions in 2021. These alarming statistics highlight the urgent need for the industry to adopt sustainable practices to mitigate its environmental impact. A fundamental step in this transition is the ability to accurately predict a project's carbon footprint, which enables stakeholders to implement effective strategies for reducing emissions throughout a building's lifecycle.

Carbon footprint estimation is typically categorized into embodied and operational carbon [2]. Embodied carbon refers to emissions generated during material extraction, production, transportation, and construction, while operational carbon arises from energy consumption during a building's use phase, including heating, cooling, and lighting [3]. Traditional methods such as life cycle assessment (LCA) and benchmark-based calculations have been widely used for carbon footprint estimation. However, these methods are often time-consuming and susceptible to inaccuracies due to data variability and inconsistencies [4]. Therefore, advanced computational techniques such as machine learning offer a promising alternative for improving prediction accuracy and efficiency.

Machine learning models have been increasingly applied in construction to analyze large datasets and identify patterns in carbon emissions [5-7]. Previous studies have demonstrated the potential of support vector regression (SVR) [8-10] and artificial neural networks (ANNs) [11, 12] in predicting carbon footprints for various building types. For instance, Chu and Zhao [13] utilized SVR to estimate the operational carbon footprint of residential buildings, while Wei, et al. [14] applied ANNs to forecast the embodied carbon footprint of prefabricated structures. Despite these advancements, limited research has directly compared different machine learning models to determine the most effective approach for carbon footprint prediction in residential construction.

This study aims to address this gap by evaluating the performance of fine tree regression (Rtree) and adaptive neuro-fuzzy inference system (ANFIS) in predicting carbon footprints across different construction stages. Additionally, this research develops a user-friendly graphical interface using

MATLAB GUI, enabling stakeholders to input project details and visualize predicted carbon emissions efficiently. By conducting a structured comparison of these two machine learning techniques, this study provides valuable insights into the most effective model for accurate and reliable carbon footprint estimation in residential construction projects.

The significance of this study lies in addressing the urgent need for industry to adopt sustainable practices. Given that traditional methods for carbon footprint estimation are often time-consuming and susceptible to inaccuracies, and that limited research has directly compared different machine learning models, this research aims to address this gap. By conducting a structured comparison of RTree and ANFIS, this study provides valuable insights into the most effective model for accurate and reliable carbon footprint estimation. The findings offer substantial practical value by providing a data-driven pathway for stakeholders, which can assist architects, engineers, and project managers in evaluating the environmental impact of different construction strategies at an early stage, thereby enabling informed decisions that align with sustainability goals

II. Methodology

This study adopts a structured methodology to compare the effectiveness of RTree and ANFIS in predicting the carbon footprint of residential construction projects. The research framework consists of five key phases: data collection, data preprocessing, model development, model evaluation, and result discussion. The primary objective is to determine which machine learning model provides more accurate and reliable carbon footprint predictions, ultimately supporting sustainable construction practices.

The study considers four major stages in the building lifecycle: production, transportation, operation, and destruction. Data for each stage is collected and processed to develop predictive models using RTree and ANFIS.

The models are evaluated using multiple error metrics, including root mean squared error (RMSE), mean absolute percentage error (MAPE), and mean squared logarithmic error (MSLE). The findings provide insights into the performance of both models and offer recommendations for selecting the most effective approach.

A. Data Collection and Preparation

Accurate carbon footprint prediction in residential construction requires a comprehensive dataset encompassing various stages of a building's life cycle. The data utilized in this study includes information related to material selection, transportation, operational energy consumption, and demolition waste management. Since inconsistencies in data collection can impact model performance, a systematic approach was adopted to ensure data reliability and integrity. This section outlines the sources of data, key variables, preprocessing techniques for standardization, and the procedure for splitting the dataset into training and testing subsets for machine learning model development.

The dataset used in this study was compiled from multiple research publications and industry reports on carbon emissions in residential construction projects. The primary variables considered include emissions from the construction stage (U_{con}), transportation stage (U_{mt}), operational stage (U_{ope}), and demolition stage (U_{dem}). The total carbon footprint (U_{tot}) was calculated as the sum of emissions across these stages expressed as Equation (1).

$$U_{tot} = U_{con} + U_{mt} + U_{ope} + U_{dem} \quad (1)$$

Each stage was further defined by specific input variables, such as material production emissions $\sum W_{mp,i} S_{mp,i}$ (in MPa), fuel consumption during transportation $\sum S_{mt} FC$ (in km/L), and operational energy consumption $(N_{oa} + N_{ol} + N_{oe}) S_{ele}$ where S_{ele} represents energy efficiency coefficients.

The demolition stage was estimated as a percentage of the initial construction emissions using the equation $U_{dem} = 0.1 \times U_{con}$ [5]. Table 1 presents the ranges of key variables used in the dataset.

Table 1: Ranges of Key Variables in the Dataset

Variable	Minimum Value	Maximum Value
U_{con} (MPa)	11000	414670
U_{mt} (km/L)	2.06	17.82
U_{ope} (kWh)	2949	26000
U_{dem} (kg CO_2)	88.93	239

Before the data could be utilized for machine learning, it underwent cleaning and standardization to eliminate inconsistencies and ensure comparability across different sources. Missing values were addressed using linear interpolation, particularly for emission factors that varied between studies. Standardization was performed by scaling the variables to a uniform range, ensuring that all numerical features were normalized between their respective minimum and maximum values. This preprocessing step prevented certain variables from disproportionately influencing the model due to their larger numerical scales. Additionally, outliers were examined and removed to improve prediction accuracy and model stability.

Once the dataset was cleaned and standardized, it was split into training and testing subsets to develop and evaluate the machine learning models. An 80/20 ratio was used, where 80% of the data (1,600 samples) was allocated for training, and the remaining 20% (400 samples) was reserved for testing. The training dataset was used to optimize model parameters and learn patterns, while the testing dataset provided an unbiased evaluation of the model's predictive accuracy. This division ensured that the models could generalize well to unseen data, reducing the risk of overfitting. The RTree and

ANFIS models were trained separately, with hyperparameter tuning applied during cross-validation to enhance predictive performance.

B. Machine Learning Model Development

To enable accurate prediction of carbon emissions in residential construction projects, two supervised machine learning techniques were selected for evaluation: RTree and ANFIS. These models were chosen due to their proven performance in nonlinear regression problems and their ability to handle complex datasets with diverse input variables [15, 16]. Both models were implemented using MATLAB, and each was trained and tested using a dataset comprising carbon emissions data from various life cycle stages. The purpose of developing these models was to compare their predictive performance in estimating total and stage-specific carbon footprints, ultimately identifying the most suitable approach for sustainable construction forecasting.

The RTree model is a type of decision tree regression algorithm that recursively partitions the dataset into smaller subsets by identifying optimal split points [17]. The tree structure is formed by choosing features and thresholds that minimize variance within the target variable, in this case, the carbon footprint. During model training, hyperparameters such as the leaf size and maximum depth were tuned using a five-fold cross-validation approach. This iterative process helped reduce overfitting and improved generalization [18]. The model was developed and tested across all life cycle stages, which are construction, transportation, operation, and demolition, as well as for the total emissions. Figure 1 illustrates the structure of a typical RTree used in this study, where decision nodes represent feature conditions and terminal nodes represent predicted carbon emission values.

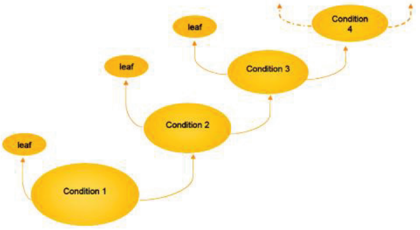

Figure 1: Structure of Fine Tree Regression Model

The adaptive neuro-fuzzy inference system combines neural network learning capabilities with fuzzy logic principles to model complex nonlinear relationships between input and output variables [19, 20]. ANFIS is structured with layers that include fuzzification of inputs, rule evaluation, and output defuzzification. In this study, the ANFIS model was trained using the same dataset as the RTree model, segmented across different construction stages. Triangular membership functions were used to define fuzzy sets for input variables, and the number of membership functions was optimized to balance model complexity and accuracy. During training, the system learned the optimal parameters for each fuzzy rule using a hybrid learning algorithm that combined gradient descent and least squares estimation. Figure 2 provides a schematic overview of the ANFIS architecture used for prediction.

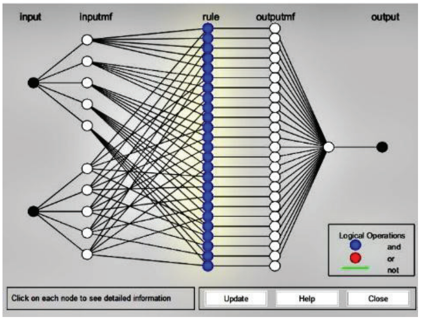

Figure 2: ANFIS Architecture for Carbon Emission Prediction

C. Model Evaluation Metrics

The effectiveness of a predictive model is contingent on how accurately it can estimate values when applied to previously unseen data. In this study, the performance of the RTree and ANFIS models was assessed using four widely recognized evaluation metrics. These include MAE, RMSE, MAPE and MSLE. Each metric provides a unique perspective on the deviation between predicted and actual carbon emission values. The combination of these metrics offers a comprehensive assessment of both absolute and relative prediction errors, allowing for a robust comparison of model performance across different stages of the residential building life cycle.

The MAE quantifies the average magnitude of errors between predicted values and actual observations. It is a straightforward and interpretable metric that measures the absolute deviation without considering the direction of the error. MAE is particularly valuable for understanding how much, on average, the model's predictions deviate from true values. It is defined mathematically as Equation (2).

$$\boldsymbol{MAE = \frac{1}{n}\sum_{i=1}^{n}|y_i - \hat{y}_i|} \quad (2)$$

where:
y_i = actual value
$\hat{y}_i$ = predicted value
n = number of observations

A lower MAE indicates a more accurate model, and because it is not sensitive to outliers, it provides a balanced view of average error magnitudes. The RMSE measures the square root of the average squared differences between the predicted and actual values. Unlike MAE, RMSE penalizes larger errors more heavily due to the squaring of residuals, making it particularly useful when large deviations are undesirable. The formula for RMSE is shown in Equation (3).

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(y_i - \hat{y}_i)^2} \quad (3)$$

RMSE is often used in regression analysis as a key indicator of model performance, especially when higher precision is needed. A model with a lower RMSE value demonstrates a stronger capability to predict carbon emissions with minimal large-scale error fluctuations.

The MAPE expresses the prediction error as a percentage, providing insight into the relative size of the error in comparison to the actual values. MAPE is particularly valuable in real-world applications where understanding the error in percentage terms aids in interpretability. The formula for MAPE is shown in Equation (4).

$$MAPE = \frac{100\%}{n}\sum_{t=1}^{n}\left|\frac{A_t - F_t}{A_t}\right| \quad (4)$$

where:
A_t = actual values at time (t)
F_t = forecasted values at time (t)

While MAPE is intuitive, it can be sensitive when actual values are very small, which can distort the percentage error. Nevertheless, it remains one of the most widely used metrics for evaluating forecasting models, particularly in sustainability assessments.

The MSLE evaluates the ratio between the actual and predicted values on a logarithmic scale. This metric is particularly suitable for datasets where values span multiple orders of magnitude or when the goal is to penalize underestimations more gently than overestimations. The MSLE formula is Equation (5).

$$MSLE = \frac{1}{n}\sum_{t=1}^{n}\begin{pmatrix}\log(1+A_t)\\-\log(1+F_t)\end{pmatrix}^2 \quad (5)$$

By transforming both actual and predicted values using the logarithmic function, MSLE captures relative differences and is less sensitive to large absolute errors. This makes it especially relevant in the context of carbon footprint prediction, where emission values can vary substantially between construction stages and projects. Lower MSLE values signify that the model is effective at capturing proportional differences, which is essential for accurate long-term sustainability forecasting.

D. Hyperparameter Optimization

The accuracy and generalizability of machine learning models can be significantly influenced by the configuration of their internal parameters, known as hyperparameters. These parameters are not learned during the training process but must be defined prior to model training. Hyperparameter optimization involves systematically tuning these values to enhance predictive performance. For this study, both the RTree and ANFIS models underwent optimization procedures tailored to their respective architectures. By applying cross-validation and iterative testing, the models were refined to achieve optimal accuracy across all stages of the residential building life cycle. For the RTree model, the key hyperparameters included the minimum leaf size and the maximum number of splits. A five-fold cross-validation approach was employed to assess model performance across different configurations, ensuring the selection of parameters that minimized the risk of overfitting. For the ANFIS model, the optimization focused on the number and type of membership functions used in the fuzzy inference system. Triangular membership functions (trimf) were selected for their balance between simplicity and modeling capacity, and the number of fuzzy rules was adjusted accordingly. The results of the hyperparameter tuning are summarized in Table 2, which presents the best-performing configurations based on RMSE and MSE across different life cycle stages.

Table 2 demonstrates that ANFIS consistently achieved lower RMSE and MSE values across all stages compared to the RTree model. This outcome highlights the effectiveness of ANFIS in capturing nonlinear relationships through its hybrid neuro-fuzzy architecture. Moreover, the optimization process confirmed the importance of selecting appropriate hyperparameters to ensure precise and reliable carbon footprint predictions in residential construction contexts.

Table 2: Optimized Hyperparameters and Performance Metrics for Fine Tree and ANFIS Models

Stage	Model	Optimized Parameter(s)	RMSE	MSE
Construction	RTree	Leaf size = 50	0.514	1.53×10^{-12}
Transportation	RTree	Leaf size = 30	447.07	6.53×10^{-8}
Operational	RTree	Leaf size = 15	1179.3	5.18×10^{-7}
Demolition	RTree	Leaf size = 50	0.061	1.74×10^{-15}
Total	RTree	Leaf size = 50	1608.6	1.47×10^{-4}
All Stages	ANFIS	Membership function = trimf	0.000 – 0.013	1.53×10^{-12} – 1.47×10^{-4}

III. Results and Discussion

This section presents a comparative analysis of the RTree and ANFIS across all major stages of a residential building's life cycle. The performance of each model was evaluated using four key metrics: MAE, RMSE, MAPE, MSLE. These metrics allow for a robust assessment of prediction accuracy, enabling identification of the most effective model for estimating carbon emissions. The discussion is organized by construction stages, providing insights into model behavior under varying conditions and data distributions. Figures accompanying each subsection illustrate metric values for visual comparison.

A. Comparison of Model Performance Across Construction Stages

In the production stage, the ANFIS model consistently outperformed the RTree model across all evaluation metrics. As shown in Figure 3, ANFIS achieved lower MAPE and MSLE values, indicating its superior ability to generalize patterns from the training data and deliver more accurate predictions. The MAPE of ANFIS was significantly lower, suggesting that its relative error was smaller than that of RTree. Similarly, MSLE values revealed that ANFIS handled variations in scale more effectively, maintaining stability even when the emission values ranged widely. These results suggest that ANFIS is more capable of capturing the nonlinear relationships that characterize material production emissions, which are often influenced by multiple interacting factors such as material type, volume, and energy intensity.

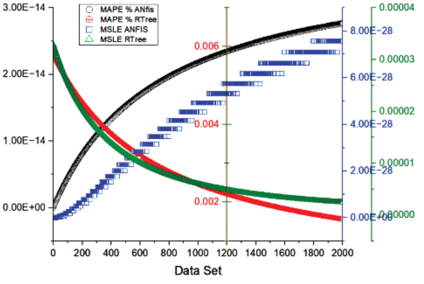

Figure 3: Comparison of ANFIS and RTree Model Performance in the Production Stage

In the transportation stage, a similar trend was observed. ANFIS again demonstrated better predictive performance than the RTree model, as illustrated in Figure 4. The transportation stage involves emissions generated from the movement of construction materials to site locations, which often varies depending on fuel efficiency, vehicle type, and transportation distance. ANFIS, with its fuzzy logic capabilities, proved more effective in managing this variability.

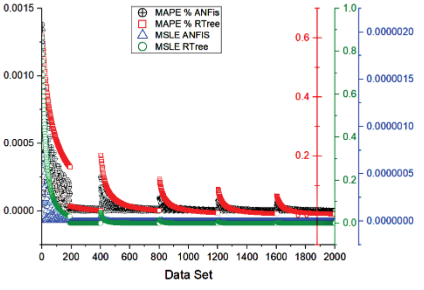

Figure 4: Model Evaluation at the Transportation Stage Using MAPE and MSLE Metrics

The RMSE and MAPE values were consistently lower for ANFIS, confirming that it produced more accurate forecasts with fewer large errors. In contrast, the RTree model showed slightly higher variability in predictions, which could be attributed to its deterministic partitioning strategy that may not capture nuanced changes in input parameters.

During the operational stage, which accounts for long-term energy consumption such as lighting, heating, and cooling, ANFIS once again outperformed RTree, as shown in Figure 5.

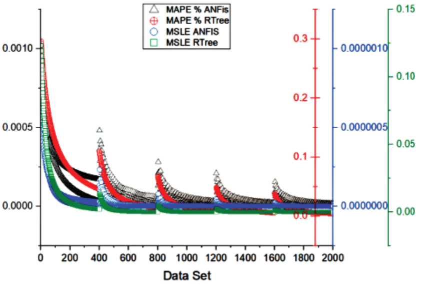

Figure 5: Performance of ANFIS and RTree Models in the Operational Stage

The difference in model accuracy became more pronounced in this phase due to the complex interplay between occupancy behavior, appliance efficiency, and energy demand. ANFIS maintained lower MAPE and MSLE values across most of the test samples, suggesting it could better approximate the time-dependent and usage-based characteristics of operational emissions. RTree, although competent, showed an increase in both absolute and percentage-based errors in this stage, reflecting its limited adaptability to continuous temporal trends within operational datasets.

In the demolition stage, both models exhibited relatively close performance, given the more predictable nature of end-of-life building activities. However, as depicted in Figure 6, ANFIS still achieved slightly lower RMSE and MAPE values than RTree.

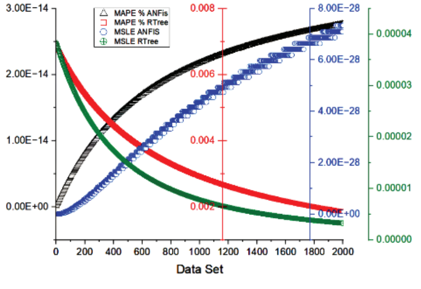

Figure 6: Evaluation of Carbon Emission Prediction Accuracy in the Demolition Stage

The demolition stage typically involves repetitive processes such as material removal, waste handling, and site clearing, which tend to generate emission patterns with lower variance. Despite the smaller performance gap, ANFIS demonstrated greater consistency in prediction, likely due to its ability to model even minor nonlinear fluctuations through its fuzzy inference mechanism. RTree, in contrast, performed adequately but with slightly larger deviations from actual values in certain test instances.

In the overall carbon footprint estimation, which aggregates emissions across all life cycle stages, ANFIS clearly emerged as the more robust model. Figure 7 illustrates a substantial reduction in both MAPE and MSLE when using ANFIS compared to RTree. The integrated nature of total emissions increases the complexity of the prediction task, as it involves cumulative uncertainties and interactions across stages. ANFIS, trained on multidimensional inputs spanning the entire building process, demonstrated superior ability to model these interactions. Its low RMSE and MSE values confirm its overall accuracy, making it a more reliable tool for practitioners aiming to forecast total environmental impact. In contrast, RTree, while interpretable and easier to implement, was more susceptible to compounded errors across the stages, resulting in less precise total emissions predictions.

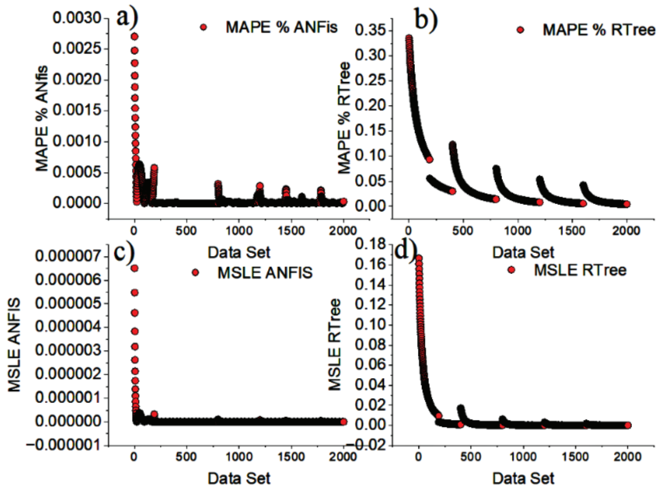

Figure 7: Total Carbon Footprint Prediction Accuracy Across All Life Cycle Stages a) MAPE for ANFIS, b) MAPE for Rtree, c) MSLE for ANFIS, and d) MSLE for Rtree

B. Model Strengths and Weakness

The comparative analysis between the RTree and ANFIS models revealed distinct strengths and limitations inherent to each approach. ANFIS consistently outperformed RTree cross all life cycle stages, particularly in scenarios involving complex, nonlinear relationships among input variables. This advantage can be attributed to ANFIS's hybrid architecture, which combines the learning capability of neural networks with the interpretability of fuzzy inference systems. As a result, ANFIS demonstrated a higher degree of flexibility and accuracy in modeling emission patterns that vary due to factors such as energy consumption, construction material diversity, and user behavior in operational stages.

One of the most notable strengths of ANFIS is its adaptability to uncertainty and imprecision in input data. In the context of carbon footprint prediction, where input parameters are often derived from heterogeneous sources or subject to estimation, this characteristic allows for more robust performance. Furthermore, the model's capacity to learn complex patterns during training enables it to generalize effectively across diverse project scenarios. However, this sophistication comes at the cost of increased computational complexity. Training ANFIS requires careful tuning of membership functions and fuzzy rules, and the model may become computationally intensive as the number of input features increases.

On the other hand, the Fine Tree model offers several practical advantages, particularly in terms of simplicity and interpretability. Its decision-tree structure provides a clear and intuitive representation of how input features influence the predicted output, making it useful for practitioners seeking transparency in their decision-making tools. The Fine Tree model also trains relatively quickly and performs well when the relationship between inputs and outputs is more linear or when datasets are relatively clean and structured. Nevertheless, its performance was generally inferior to that of ANFIS, particularly in handling high-dimensional data and capturing subtle interactions between features. The tendency of decision trees to overfit or underfit, especially when hyperparameters are not optimally tuned, further limited the RTree model’s predictive accuracy.

In summary, while both models are viable for carbon footprint prediction, ANFIS presents a more powerful solution for complex and variable construction datasets, whereas RTree may be more appropriate for straightforward applications requiring speed and interpretability. The choice of model should therefore be guided by the specific requirements of the project, including the nature of the data, computational resources available, and the desired balance between accuracy and transparency.

C. Practical Implications for Sustainable Construction

The findings of this study offer substantial practical value for advancing sustainable practices within the construction industry, particularly in the domain of residential development. By demonstrating the superior performance of the ANFIS model over the Fine Tree regression approach in predicting carbon emissions across various life cycle stages, this research provides a data-driven pathway for stakeholders to integrate intelligent forecasting tools into their planning and design workflows. The predictive capabilities of ANFIS can assist architects, engineers, and project managers in evaluating the environmental impact of different construction strategies at an early stage, thereby enabling informed decisions that align with sustainability goals.

Moreover, the implementation of a user-friendly interface through MATLAB GUI, as developed in this study, facilitates broader accessibility and practical deployment of the model. This tool can be utilized by professionals without advanced programming expertise, allowing seamless input of project specifications and real-time visualization of projected carbon footprints. Such integration empowers decision-makers to identify carbon-intensive phases, compare alternative materials or methods, and prioritize emissions reduction strategies in accordance with regulatory standards and environmental certifications, such as LEED or GreenRE.

The use of machine learning models also supports compliance with emerging national and international climate policies, as governments increasingly mandate carbon accounting and emission limits in the built environment. The models presented here can serve as part of a larger digital toolkit for green construction, where simulation and optimization are key to minimizing both embodied and operational carbon. By providing rapid and accurate feedback on design scenarios, this study enables a shift from reactive to proactive sustainability planning, thereby reinforcing the construction sector's role in climate action and environmental stewardship.

IV. Conclusion

This study presented a comparative analysis of two machine learning approaches which are RTree and ANFIS for predicting carbon footprints across the life cycle stages of residential construction projects. The results demonstrated that ANFIS consistently outperformed the Fine Tree model in terms of accuracy, generalization, and robustness, as evidenced by lower error rates across multiple evaluation metrics including MAE, RMSE, MAPE, and MSLE. The ANFIS model's hybrid architecture enabled it to effectively capture nonlinear relationships and manage uncertainties inherent in construction-related datasets. In contrast, while the Fine Tree model offered benefits in terms of simplicity and interpretability, its predictive performance was generally lower, particularly in stages with complex emission dynamics. By integrating the optimized ANFIS model into a MATLAB-based graphical user interface, this study also contributes a practical tool that can support sustainability-focused decision-making in real-world construction settings. Overall, the findings underscore the potential of advanced machine learning techniques to enhance environmental assessment in the built environment, thereby promoting more sustainable and data-driven construction practices.

V. Acknowledgement

The authors gratefully acknowledge the financial support provided by the TVET Applied Research Grant Scheme under Grant No. T-ARGS/2024/BK01/00076. This support was instrumental in facilitating the research activities, data analysis, and model development presented in this study. The authors also extend their appreciation to the Department of Civil

Engineering at Politeknik Ungku Omar for providing the academic resources and technical guidance necessary to complete this work.

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