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A comparative analysis of artificial intelligence techniques for carbon emission predictions in the construction industry

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The construction industry significantly contributes to global carbon emissions, necessitating urgent mitigation measures. This study addresses the challenge of predicting carbon emissions during construction projects using advanced artificial intelligence (AI) techniques. The performance of two AI models, Random Forests (RF) and Support Vector Machines (SVM), is compared to determine their effectiveness in forecasting emissions based on construction materials, techniques and project scale. Predictive models were developed using a dataset derived from previous research and real-world construction site data, ensuring accuracy through meticulous pre-processing, including data cleaning, normalization, and feature selection. The RF and SVM models were trained and tested on this dataset to evaluate their performance. The results show that the models achieve significant accuracy, and the RF model slightly outperforms the SVM in precision and reliability. This study underscores the potential of AI-driven approaches to improve sustainability in the construction industry. Insights from the analysis can inform industry stakeholders and policymakers in developing effective carbon reduction strategies, aligning with global efforts to combat climate change.

Keywords: *carbon emissions prediction; artificial intelligence in construction; random forests; support vector machines; sustainability in construction; carbon reduction strategies.*

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1. Introduction

The construction industry is a major contributor to global carbon emissions, accounting for around 13% of the world's GDP, with projections of increasing to 15% by 2020 [1]. This significant impact is primarily due to the embodied carbon dioxide in key construction materials such as cement and steel [2]. Addressing carbon emissions in construction is vital not only for environmental protection but also for meeting international climate goals and ensuring long-term economic sustainability. From a disciplinary perspective, civil and environmental engineering have increasingly focused on developing innovative methods to reduce the carbon footprint of construction activities. Advanced technological solutions, particularly in artificial intelligence (AI), offer promising avenues for enhancing the accuracy and efficiency of carbon emission predictions, which are essential for informed decision-making and policy development.

Artificial intelligence has shown significant promise in predicting energy consumption in buildings, which closely correlates with carbon emissions [3]. In recent years, researchers have proposed various machine learning models in AI to predict carbon emissions. Advanced AI techniques, particularly Random Forest (RF) and Support Vector Machines (SVM), have been widely used to improve the

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accuracy and efficiency of carbon emission forecasts. One of the most significant efforts researchers have made is utilization o a RF model based on graph factors to evaluate and predict carbon emission patterns in Pearl River Delta cities [4]. Meanwhile, Extreme RF integrated with additional data has been used to reconstruct carbon emission data sets with high determination coefficients, highlighting their effectiveness in improving forecast accuracy [5]. Past researchers have also made several attempts to compare with traditional methods such as multiple linear regression [6], linear regression [7,8], and lasso regression [9] to predict carbon emissions, and it was found that RF is powerful in predicting high accuracy. In studying the use of machine learning techniques, Kim et al. [10] developed a method to measure carbon dioxide emissions from concrete production, while another study analyzed the global construction industry using data from various regions to identify ways to reduce greenhouse gas emissions [11]. These advances highlight RF's important role in improving the accuracy of carbon emissions forecasts and promoting sustainable practices.

Over the past few years, SVMs have been used to analyze historical data, uncover patterns, and make predictions for new data [12]. It has been effectively utilized in predicting carbon emissions from construction activities, demonstrating high interpretability and low average error in modeling embodied carbon emissions at the design stage [13]. In a different study, SVM was found to outperform linear methods in predicting city-level carbon emissions, exhibiting higher prediction accuracy and lower errors [14]. Previous studies have compared SVM and Decision Tree (DT) models [15]. They found that SVM offers faster learning and robust generalization, depending on hyper-parameters such as the penalty coefficient. On the other hand, DT requires careful iterative control to avoid over-fitting. Although this AI approach is mostly performed as a single model, offering advantages in simplicity, efficiency, and ease of implementation, it may fail to capture complex patterns and face challenges such as long training time and over-fitting. Previous studies have yet to fully explore the wide-ranging application of AI techniques in various construction scenarios. They have often focused on limited datasets or single methods, leading to a lack of understanding about the best AI model for predicting carbon emissions in construction projects, given the numerous influencing factors. Furthermore, there is a debate about the effectiveness of AI in predicting carbon emissions, while others emphasize the reliability and accuracy of SVM in handling complex non-linear data. These differing perspectives highlight the importance of conducting a comparative analysis to identify the most dependable model for predicting carbon emissions in the construction industry.

This study aims to bridge the existing knowledge gap by comparing the efficacy of RF and SVM models in predicting carbon emissions during construction projects. With a dataset calculated from equations from previous studies, the research rigorously pre-processed the data to ensure accuracy. The pre-processing steps included data cleaning, normalization, and feature selection. Subsequently, the models were trained and tested on this dataset to comprehensively evaluate their performance. The primary objective of this research is to provide a clear, comparative analysis of RF and SVM models, emphasizing their strengths and weaknesses in the context of carbon emission predictions in construction. By offering insights into the most effective artificial intelligence techniques, this study aims to inform industry stakeholders and policymakers, facilitating the development of robust carbon reduction strategies that align with global efforts to combat climate change. The significance of this study lies in its potential to enhance sustainability practices within the construction industry, thereby contributing to broader environmental and economic benefits. However, the study is limited by the scope of its dataset and the specific AI models analyzed. Future research should consider a broader range of models and more extensive datasets to validate and expand upon these findings.

2. Methodology

This study uses a comparative methodology to evaluate the effectiveness of two prominent artificial intelligence techniques, RF and SVM, in predicting carbon emissions in the construction industry. The focus is on understanding how various machine learning models can interpret and utilize construction-related data to accurately predict emissions.

2.1. Dataset and pre-processing

The dataset for this study was constructed using the calculation results of Equation (1) [16], which quantifies carbon emissions (CE) from construction activities by incorporating various parameters. The parameters included the quantity of construction machinery or plant (M_j) the carbon emission factor per unit fuel or power consumption (F_j) the number of operational hours (h_j), and the rate of fuel or electricity consumption (r_j). These parameters were collected from a range of building sites, ensuring a comprehensive and representative dataset. Table 1 outlines the range of input values used in these calculations: M_j ranges from 1 to 5 units, r_j ranges from 500 to 1000 liters per hour (L/h) or kilowatt-hours (kWh), h_j ranges from 8 to 18 hours, and F_j ranges from 0.5 to 3 kilograms of CO2 equivalent per liter (kgCO2e/L) or per kilowatt (kgCO2e/kW),

$$\mathrm{CE} = \sum_{j=1}^{n} M_j \times r_j \times h_j \times F_j. \tag{1}$$

Table 1. Range of parameter input values.

Input parameter	Range
M_j	1–5
r_j (L/h) or (kW/h)	500–1000
h_j	8–18
F_j (kgCO2e/L) or (kgCO2e/kW)	0.5–3

To ensure the accuracy and reliability of the machine learning models, the dataset underwent a meticulous pre-processing phase. The data was first cleaned to address any inconsistencies or missing values, which were imputed using statistical methods. The next step involved normalizing the data to standardize the scale of the variables, facilitating effective algorithm performance. Categorical variables, such as types of machinery, were encoded numerically using techniques like one-hot encoding. Feature selection methods were employed to identify the most influential variables affecting carbon emissions, thereby reducing the dataset's dimensionality and improving model efficiency. The pre-processed dataset was then divided into training and testing subsets, maintaining an even distribution of variables. This thorough preparation enabled the development of robust predictive models using RF and SVM algorithms, which are crucial for devising strategies to mitigate carbon emissions in the construction industry.

2.2. Random forest model development

The RF model is a robust non-parametric ensemble learning technique widely recognized for its predictive accuracy and versatility in handling complex datasets. Random forests are particularly well-suited for regression and classification tasks [17], making them an ideal choice for predicting carbon emissions in the construction industry. This model aggregates the predictions of multiple decision trees, which are trained on different subsets of the data, to produce a final prediction that is more accurate and reliable than that of any single decision tree [18]. The ability of RF to handle large datasets with higher dimensionality, combined with their resistance to over-fitting, makes them a powerful tool in environmental modeling and analysis.

Table 2. Range of hyperparameter values for RF.

Hyperparameter	Range
Number of trees	100–1000
Maximum depth	10–50
Minimum samples split	2–10
Minimum samples leaf	1–5
Bootstrap	True/False

This study utilized RF to leverage its ensemble learning capabilities to develop a highly accurate model for predicting carbon emissions from construction activities. By employing RF, the study aims to capture the complex relationships between various factors such as construction materials, machinery, operational hours, and fuel consumption. This approach enhances prediction accuracy and provides insights into the relative importance of different variables affecting carbon emissions. The RF model is a powerful tool that operates on the principle of creating a 'forest' composed of multiple decision trees, each built using a random subset of the training data. This approach ensures that the model is less likely to overfit the training data and can generalize well to unseen data [19]. The network structure of the RF consists of numerous parallel decision trees, each contributing to the overall prediction. This ensemble approach guarantees robustness and accuracy in handling complex data sets. With its ability to aggregate predictions from multiple trees, the RF model is ideal for classification and regression tasks, making it a versatile and reliable choice for predictive modeling.

To predict carbon emissions using the RF model, we follow several key steps. First, we divide the pre-processed dataset into training and testing subsets. During model training, we train the RF model on the training subset and tune several hyper-parameters, including the number of trees, the maximum depth of each tree, the minimum number of samples required to split an internal node, the minimum number of samples required to be at a leaf node, and whether bootstrap samples are used when building trees. To optimize model performance, we conduct hyper-parameter tuning using techniques like grid search or random search. The detailed range of hyper-parameters and the number of regression trees used in this study are provided in Table 2, with the optimum configuration determined based on cross-validation results, balancing model complexity and predictive performance.

2.3. Support vector machine model development

Support Vector Machines is a set of supervised learning methods for classification, regression, and outlier detection [20]. In this study, we focus on Support Vector Regression (SVR), an adaptation of the SVM for regression tasks. SVR is well-regarded for its robustness and accuracy in capturing complex relationships in data, making it a suitable choice for predicting carbon emissions in the construction industry. Unlike traditional regression techniques, SVR aims to find a hyperplane in a high-dimensional space that best fits the data points while minimizing the prediction error within a specified threshold. SVR is distinguished by its ability to model non-linear relationships and handle high-dimensional datasets efficiently [21]. This capability makes SVR particularly useful for predicting carbon emissions, as it adeptly manages the trade-off between model complexity and prediction accuracy. This is crucial because the relationship between input variables and emissions is often non-linear and influenced by numerous factors.

The SVR principle involves mapping the input features into a high-dimensional feature space using a kernel function, where a linear regression model is constructed. Key steps in SVR include the kernel trick, optimization objective, and support vectors. The kernel trick allows SVR to utilize kernel functions to transform data into a higher-dimensional space, capturing non-linear relationships [22]. Commonly used kernels include linear, polynomial, radial basis function (RBF), and sigmoid [23]. The optimization objective in SVR is to minimize the ε-insensitive loss function, which penalizes prediction errors only if they exceed a certain threshold (ε), helping to construct a model that is robust to outliers and noise. Support vectors, a subset of the training data points that lie closest to the hyperplane, are used to define the model's parameters. The architecture of the SVR model centers around these support vectors and the kernel function, collectively enabling the model to predict new data points accurately.

Table 3. Range of hyperparameter values for SVR.

Hyperparameter	Range
Kernel function	Linear, RBF, Polynomial, Sigmoid
Regularization (C)	0.1–1000
Epsilon (ε)	0.001–1
Gamma (γ)	0.0001–1
K-fold cross-validation	5–10

In this study, implementing the SVR model to predict carbon emissions involves several key steps. First, the pre-processed dataset, which has been cleaned, normalized, and encoded, is divided into training and testing subsets. During model training, the SVR model is trained on the training subset, with several hyper-parameters tuned, including the kernel function (linear, polynomial, RBF, or sigmoid), the regularization parameter (C), which controls the trade-off between achieving a low error on the training data and minimizing model complexity, epsilon (ε), which specifies the margin within which no penalty is given to errors, and gamma (γ), which defines the influence range of a single training example for RBF, polynomial, and sigmoid kernels. Hyper-parameter tuning is conducted using techniques like grid search or random search, with K-fold cross-validation ensuring robust performance assessment. The range of hyper-parameters and tuning parameters used in this study are detailed in Table 3, with the optimum configuration determined based on cross-validation results, balancing model complexity, and predictive performance.

2.4. Model performance evaluation method

Evaluating the performance of predictive models is a crucial step in the modeling process, as it helps in understanding the accuracy and reliability of the models. In this study, we employ four metrics to assess the performance of the RF and SVM models in predicting carbon emissions: Coefficient of Determination (R^2), Root Mean Squared Error (RMSE), Mean Squared Error (MSE), and Mean Absolute Percentage Error (MAPE). The R^2, as defined in Equation (2), measures the proportion of the variance in the dependent variable that is predictable from the independent variables, ranging from 0 to 1, with higher values indicating better model performance. The R^2 value close to 1 signifies that the model explains most of the variability in the response data. RMSE, as defined in Equation (3), is the square root of the average of the squared differences between the predicted and actual values, providing a measure of the model's prediction error expressed in the same units as the dependent variable; lower RMSE values indicate more accurate predictions. MSE, as defined in Equation (4), is the average of the squared differences between the predicted and actual values, giving a sense of the magnitude of the prediction error, with lower MSE values indicating better model performance. As defined in Equation (5), MAPE measures the model's accuracy as a percentage by taking the average of the absolute percentage errors between the predicted and actual values. MAPE is particularly useful for comparing prediction accuracy across different datasets, significantly when the scales of the dependent variable vary, with lower MAPE values indicating higher accuracy. These metrics provide comprehensive insights into the models' predictive capabilities, highlighting their strengths and weaknesses,

$$R^2 = \left(\frac{\sum_{i=1}^{N} (p_i - \bar{p})(t_i - \bar{t})}{\sqrt{\left[\sum_{i=1}^{N} (p_i - \bar{p})^2\right]\left[\sum_{i=1}^{N} (t_i - \bar{t})^2\right]}} \right)^2, \tag{2}$$

$$\text{RMSE} = \sqrt{\frac{1}{N}\sum_{i=1}^{N} (t_i - p_i)^2}, \tag{3}$$

$$\text{MAE} = \frac{1}{N}\sum_{i=1}^{N} |t_i - p_i|, \tag{4}$$

$$\text{MAPE} = \frac{100}{N}\sum_{i=1}^{N} \frac{|t_i|}{|p_i|}, \tag{5}$$

where p_i and $\overline{p}$ are the predicted and average predicted values, while t_i and $\overline{t}$ signify the observed and average observed values, respectively.

3. Results and discussion

In this section, we thoroughly analyze the performance of two advanced AI techniques, which is RF and SVM, in predicting carbon emissions within the construction industry. This analysis is based on a robust dataset that includes detailed parameterization of construction activities to gain a precise understanding of carbon outputs. Our findings, derived from comparing calculated and predicted emissions values, are crucial for evaluating the effectiveness of these models.

In Figure 1, a scatter plot compares calculated and predicted carbon emissions using RF and SVM during training and testing. For the RF model, there is a strong correlation between estimated and predicted values, especially during the training phase, where the R^2 value reaches 0.9834, indicating nearly perfect prediction accuracy. The testing phase shows slightly reduced accuracy with an R^2 of 0.8642, demonstrating robust predictive capability. The RMSE value during the training phase is impressively low at 0.0617, further validating the RF model's accuracy in predicting carbon emissions. The SVM model also performs well, with consistent R^2 values of 0.8046 in training and 0.8108 in testing, indicating strong model performance across different datasets. The RMSE score for SVM

reflects slightly less accuracy than RF, with values of 0.1465 in training, improving to 0.1090 in the testing phase, respectively. These results highlight the effectiveness of SVM in handling complex and non-linear relationships within the data, although it does not match the RF model in sheer predictive power.

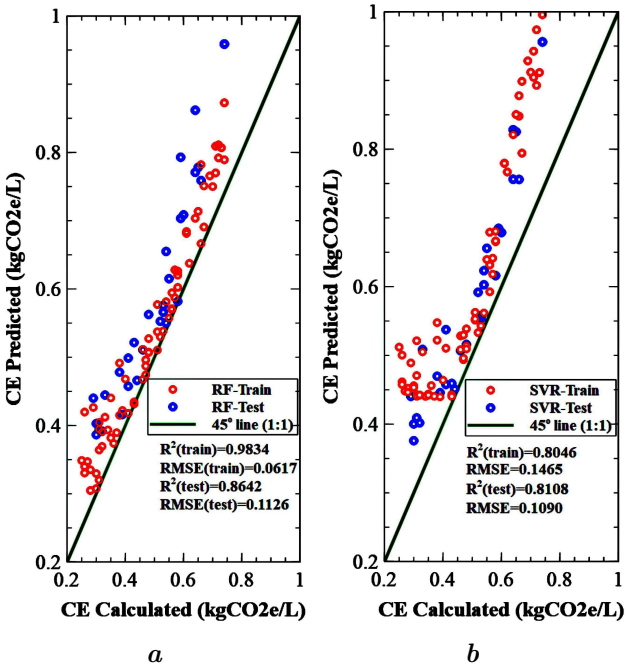

Fig. 1. Scatter plot of calculated and predicted in the train and test phase for (***a***) RF (***b***) SVR.

The performance of both RF and SVR models is detailed in Table 4 of the paper during the training and testing phases. In the training phase, the RF model demonstrates superior performance with an R^2 value of 0.9834, indicating its ability to explain 98.34% of the variance in carbon emissions from the training data. The low RMSE and MAE values of 0.0617 and 0.0498, respectively, suggest minimal deviation between predicted and actual emission values. However, the RF model's performance drops noticeably in the testing phase, with R^2 decreasing to 0.8642 and increased RMSE and MAE values, reflecting challenges in generalizing the model to unseen data. On the other hand, the SVR model maintains consistent performance between the training and testing phases, with R^2 values of 0.8046 and 0.8108, indicating good predictive accuracy. Although the RMSE and MAE values are higher for SVR compared to RF, particularly in the training phase (0.1465 and 0.1265), the testing phase shows improved error metrics (0.1090 and 0.0938), demonstrating SVR's robustness. The relatively higher MAPE values for SVR in both phases suggest that while SVR is stable, it may not capture extreme values as effectively as RF. These insights highlight the strengths and limitations of each model, providing valuable information for stakeholders interested in implementing AI-driven strategies for carbon emission reduction in the construction industry.

Table 4. Values of metrics performance in models training and test phase.

Metrics	Models			
	RF		SVR	
	Train	Test	Train	Test
R^2	0.9834	0.8642	0.8046	0.8108
RMSE	0.0617	0.1126	0.1465	0.1090
MAE	0.0498	0.0956	0.1265	0.0938
MAPE	0.1199	0.1992	0.2970	0.1993

Figure 2 shows a side-by-side scatter plot comparing the actual and predicted carbon emissions for both the RF and SVR models. This visual representation offers clear insights into the accuracy and distribution of predictions from each model across the dataset. The scatter plot for the RF model indicates a tight clustering of data points near the line of perfect prediction, showing high accuracy, especially in predicting lower and mid-range emissions values. The dense concentration of points near the line indicates that the RF model effectively captures the underlying patterns in the dataset without significant overfitting or underfitting. In contrast, the scatter plot for the SVR model exhibits a broader spread of points, suggesting a more variable performance across different emissions levels. Although the SVR model still aligns reasonably well with the line of perfect prediction, there are noticeable deviations, particularly at higher emission values. This variability indicates that SVR may struggle with the complexity and variability associated with the highest emission outputs, possibly due to its linear nature not handling the non-linear aspects of the dataset well. However, the consistency of SVR across different ranges, as seen in the similar distribution of points at both lower and higher ends, highlights its usefulness in scenarios where a balanced trade-off between accuracy and model robustness is needed.

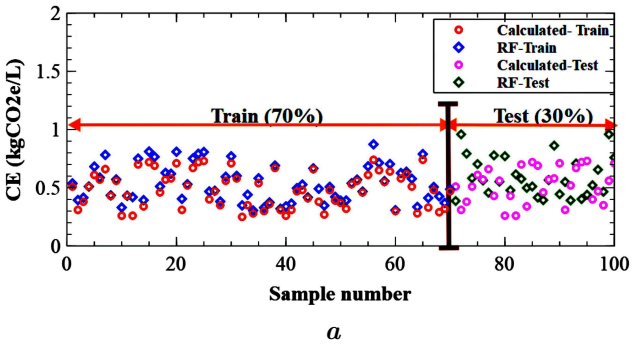

Fig. 2. Comparison scatter plot between calculated and predicted for (***a***) RF and (***b***) SVR.

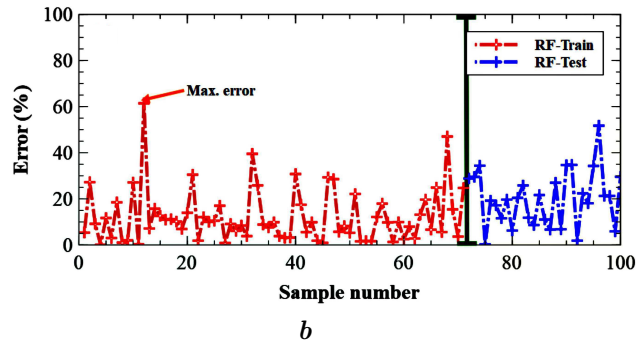

Fig. 3. Error percentage of CE prediction in the train and test for (***a***) RF and (***b***) SVR.

The graph in Figure 3 shows the error percentages of carbon emission predictions during the RF and SVR models' training and testing phases. This graph effectively illustrates the error distribution and reflects the reliability of each model under different conditions. The RF model demonstrates a significantly lower error percentage during the training phase, indicating its ability to fit the training data closely. However, there is a noticeable increase in error during the testing phase, suggesting that the model may be overfitting the training dataset, which could impact its ability to generalize to new, unseen data. This pattern is essential for understanding how the model performs in real-world scenarios, where the ability to predict new data is crucial.

On the other hand, the SVR model shows a more consistent error percentage across the training and testing phases. While the overall error rates are higher than those of the RF model in the training phase, the consistency of SVR across different datasets suggests better generalization capability. This consistent performance implies that SVR may be more reliable when applied to diverse real-world data despite not achieving as low error percentages as the RF model in a controlled training environment.

4. Conclusion

The study involved comparing the effectiveness of two AI models, RF and SVM, in predicting carbon emissions in the construction industry to promote sustainable practices. The findings showed that both models performed well, with RF slightly more precise than SVM, especially in controlled training environments. However, SVM demonstrated consistent performance across diverse datasets, making it a reliable option for practical applications. While the models have the potential to reduce the environmental impact of construction activities, they also have limitations, such as RF's tendency to overfit and SVM's occasional difficulty with complex datasets. These results highlight the importance of advanced machine learning techniques in environmental management and suggest further research to improve model accuracy and expand their applicability under different data scenarios. This study contributes to the academic discussion on sustainable construction practices and offers practical insights for industry stakeholders interested in implementing AI-driven environmental strategies.

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Порівняльний аналіз методів штучного інтелекту для прогнозування викидів вуглецю в будівельній галузі

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Будівельна галузь робить значний внесок у глобальні викиди вуглекислого газу, що вимагає термінових заходів щодо пом'якшення наслідків. У цьому дослідженні розглядається проблема прогнозування викидів вуглекислого газу під час будівельних проєктів з використанням передових методів штучного інтелекту (ШІ). Порівнюється продуктивність двох моделей штучного інтелекту, випадкових лісів (RF) і опорних векторних машин (SVM), щоб визначити їх ефективність у прогнозуванні викидів на основі будівельних матеріалів, методів і масштабу проєкту. Прогнозні моделі були розроблені з використанням набору даних, отриманого з попередніх досліджень і реальних даних будівельних майданчиків, забезпечуючи точність шляхом ретельної попередньої обробки, включаючи очищення даних, нормалізацію та вибір функцій. Моделі RF та SVM навчені та протестовані на цьому наборі даних, щоб оцінити їх продуктивність. Результати показують, що моделі досягають значної точності, а модель RF дещо перевершує SVM за точністю та надійністю. Це дослідження підкреслює потенціал підходів на основі штучного інтелекту для підвищення стійкості в будівельній галузі. Висновки, що отримані в результаті аналізу, можуть допомогти зацікавленим сторонам галузі та політикам розробити ефективні стратегії скорочення викидів вуглекислого газу, узгоджуючи їх із глобальними зусиллями по боротьбі зі зміною клімату.

Ключові слова: *прогноз викидів вуглецю; штучний інтелект у будівництві; випадкові ліси; опорні векторні машини; стійкість в будівництві; стратегії скорочення вуглецю.*