REST Publisher; ISSN No: 2583-6412 (Online)

Journal on Materials and its Characterization

journal homepage: https://restpublisher.com/journals/jmc/



Sustainable Construction: the Role of Green Building Materials in Modern Architecture

Chinnasami Sivaji*, M. Ramachandran, Sathishkumar Mani

REST Labs, Kaveripattinam, Krishnagiri, Tamil Nadu, India.

ARTICLE INFO

Article history:
Received: 01 October 2026
Accepted: 15 October 2026
Available online: 31 October 2026

Keywords:
Keywords: Sustainability
Energy Efficiency
Recycled Content
Low Emissions
Thermal Performance
Eco-Friendly

ABSTRACT

Green building materials (GBMs) play a key role in sustainable construction by reducing environmental impact, improving energy efficiency, and improving indoor air quality. With increasing concerns about resource depletion and climate change, the construction industry is moving towards materials with lower embodied energy, reduced CO emissions, and higher sustainability scores. This study examines various aspects of GBMs, including recycled content, thermal conductivity, environmental impact, and life cycle assessment. Through a comprehensive analysis, this research evaluates the performance of various materials based on key sustainability criteria. Data-driven insights suggest that materials with higher recycled content exhibit improved sustainability scores, while those with lower embodied energy and CO emissions significantly reduce their environmental footprint. In addition, thermal conductivity plays a key role in determining a material's performance in insulation, which directly impacts energy consumption for heating and cooling. Machine learning techniques including random forest regression, support vector regression, and gradient boosting were used to model and predict the sustainability performance of various GBMs.

1. INTRODUCTION

The natural origin of materials is often associated with their sustainability. However, some naturally occurring or naturally derived materials may pose risks to human health. For example, radon is a radioactive gas that can be released from certain building materials and may increase the risk of lung cancer. Asbestos was once widely used in construction but is now banned or restricted in many countries because of its carcinogenic properties. Similarly, turpentine, a solvent derived from distilled wood resins, can be harmful to human health [1].The primary objective of green building is to create environmentally responsible structures that optimize the use of water, electricity, and other resources. Green buildings contribute to healthier urban environments, lower operating costs, and improved occupant productivity [2]. Encouraging architects and construction companies to incorporate environmentally friendly features into building designs can improve their environmental performance and green building certification ratings [3].The proposed strategy is based on a modified Leadership in Energy and Environmental Design (LEED) rating system developed for evaluating buildings in Colombia, where the green building movement is still developing. Considering the constraints of the Colombian construction industry, adopting a LEED-based rating system was considered a practical initial approach to assessing green buildings [4].When evaluating sustainability criteria, the environmental impact of building materials can be reduced by selecting materials that

*Corresponding author email-id: chinnasamirsri01@gmail.com

DOI: https://doi.org/10.46632/jmc/5/4/1
Copyright @ 2026 Published by REST Publisher

require less energy, generate less waste, and cause less pollution. These choices can also indirectly improve the social and economic dimensions of sustainability [5]. Research on green building material selection aims to establish a structured knowledge base and systematic frameworks for identifying appropriate materials [6].Customer satisfaction is an important consideration when evaluating building materials and their suppliers. Property developers may improve their business performance and competitiveness by selecting green material suppliers who respond promptly and effectively to customer requirements [7].The assessment of green construction materials should consider two essential aspects. First, every stage of a material's life cycle, from raw material extraction and processing to manufacturing, use, and disposal, should be thoroughly evaluated [8]. Environmental assessment techniques can also be applied at building and community levels to improve the quality and sustainability of urban environments [9].Building materials inevitably influence human health. Environmentally friendly materials are increasingly being used as alternatives to conventional materials to reduce adverse health effects in indoor and outdoor environments [10]. Throughout their life cycles, building materials also affect the environment. Pollutants generated during raw material extraction, manufacturing, and demolition waste disposal can adversely affect air, soil, and water quality [11].Following the completion of the initial plans for the study area, passive and active green building features were selected and incorporated into the subsequent design process [12]. In South Korea, policies promoting green building materials have become increasingly important through the development of building certification programs, improvements in environmental impact assessment methods, and the strengthening of local government regulations [13].Construction activities and the associated stages of building development and operation affect the environment both directly and indirectly. Direct impacts include resource and energy consumption, waste generation, and pollution, whereas indirect impacts may arise from additional pressure on existing infrastructure 14.Many contemporary green building initiatives focus on specific environmental impacts or particular stages of a product's life cycle. A product may be considered environmentally preferable if it incorporates recycled materials or minimizes harmful contaminants, such as volatile organic compounds, during installation [15]. According to technical weighting or uniform weighting schemes, cork wool may be considered a suitable alternative, while sheep wool is frequently selected based on environmental considerations 16].The preferences of clients, brokers, contractors, engineers, and construction companies regarding the transition to green building projects in Greece have been investigated through questionnaire surveys [17]. The term "green building" encompasses a range of practices used in building design, construction, and maintenance. One important strategy involves selecting environmentally preferable building materials, including materials derived from renewable resources where appropriate 18.the terms green building (GB) and sustainable building generally refer to high-performance structures designed and constructed to improve resource efficiency [19]. Buildings are among the major consumers of energy and significant sources of greenhouse gas emissions. These emissions contribute to climate change and pose substantial challenges to environmental sustainability, highlighting the importance of sustainable building practices [20].

2. MATERIALS AND METHODS

Material

- **Recycled Content:** The percentage of components in a product that are recovered and reused from post-consumer or industrial waste is called recycled content. The use of recycled materials is essential for sustainable development, as it reduces waste, conserves natural resources, and reduces the impact on the environment. In support of circular economy policies and reducing reliance on virgin raw materials, businesses in various industries, such as manufacturing, packaging, and construction, are increasingly integrating recycled content into their products.
- **Embodied Energy:** Embodied energy is the total amount of energy needed to extract, process, produce, transport, and install the materials utilized in a product or construction. When evaluating the environmental impact of buildings, infrastructure, and consumer goods, this is a crucial factor to take into account. The energy utilized throughout a product's usage phase, as opposed to functional energy, comprises all energy inputs made during the product's whole life cycle, from raw material extraction to recycling or disposal.
- **CO2 Emissions:** Emissions of carbon dioxide (CO2) are one of the main factors contributing to global climate

change. Numerous human activities, most notably the combustion of fossil fuels like coal, oil, and natural gas, produce them. Global temperatures are rising, polar ice caps are melting, and weather patterns are becoming more severe as a result of the continuous increase in CO2 emissions since the Industrial Revolution. CO2 emissions must be addressed in order to slow down climate change and guarantee a sustainable future.

- **Thermal Conductivity:** Thermal conductivity is a crucial characteristic of materials that defines their capacity to transport heat. The rate of heat transfer through a substance per unit area per unit temperature gradient is its definition. In short, it evaluates a material's capacity to transfer heat from one place to another. The SI unit for thermal conductivity is watts per meter per kelvin (W/m·K). The following factors influence a material's thermal conductivity: Composition of the material: The amount of thermal conductivity varies between materials. Rubber and wood are poor thermal conductors, but metals such as copper and aluminum have good thermal conductivity.
- **Sustainability Score:** A sustainability score is a measure that assesses the environmental, social, and economic impacts of a system, process, or product. It provides a comprehensive assessment of sustainability performance, taking into account multiple variables, including resource efficiency, carbon footprint, ethical work practices, and economic viability. A higher sustainability score indicates a more responsible and sustainable approach, while a lower score indicates areas for improvement. Companies, policymakers, and consumers are increasingly relying on sustainability scores to guide decision-making and encourage more sustainable practices.

3. MACHINE LEARNING ALGORITHMS

Linear Regression

A basic statistical and machine learning method for simulating the relationship between a dependent variable and one or more independent variables is called linear regression. It is extensively utilized in econometrics, predictive analytics, and other domains where knowing how variables relate to one another is essential. Finding the best-fit line that reduces the discrepancy between the expected and actual values is the main objective of linear regression. A linear regression model requires a number of presumptions in order to function wellThe independent and dependent variables must first have a linear relationship. In order to prevent mistakes from being correlated, the observations must also be independent. Third, the residuals' variance must be constant, which is known as homoscedasticity. Fourth, a normal distribution for the residuals is required. Lastly, substantial multicollinearity among the independent variables is undesirable since it can skew the model's interpretation and accuracy. A linear regression model's performance is evaluated using a variety of indicators. The mean squared differences between the actual and expected values are measured by the mean squared error (MSE) and the root mean squared error (RMSE), which provide information about how accurate the prediction is. The extent to which the independent variables account for the variation in the dependent variable is shown by the coefficient of determination, also referred to as the coefficient of determination.

Random Forest Regression

Random Forest Regression is a powerful ensemble learning method for data analysis and predictive modeling. By building a large number of decision trees and averaging their predictions, this extension of decision tree regression increases accuracy and reduces overfitting. The algorithm's robustness, versatility, and ability to handle complex datasets with high dimensionality make it frequently used in a variety of fields, including engineering, healthcare, and finance. The basic idea behind random forest regression is to build a set of trained decision trees based on a randomly selected sample of data. To build each unique tree, the approach uses bootstrap samples, which are random samples with replacement. Furthermore, a random subset of attributes is selected at each tree node to identify the optimal split, add variance, and ensure diversity between trees. Compared to a decision tree, a forest of trees makes predictions by averaging the outputs of each individual tree, which makes it more reliable and accurate. One of the primary advantages of random forest regression is its ability to handle both linear and nonlinear relationships within data. Unlike conventional linear regression models that assume a linear relationship between independent and dependent variables, random forests are capable of capturing complex patterns and interactions between attributes.

Support Vector Regression

A powerful machine learning approach called support vector regression (SVR) applies the concepts of support vector machines (SVM) to regression problems. In contrast to conventional regression models, the main goal of SVR is to find a function that approximately represents the relationship between independent and dependent variables while allowing for tolerance of prediction error. This feature results in SVR's ability to handle high-dimensional data, nonlinear relationships, and noisy datasets. To capture complex interactions between variables, SVR uses kernel functions to translate the input data into a high-dimensional feature space. The algorithm then establishes a decision boundary that minimizes the error while ensuring that most of the training data points fall within the epsilon-tube, a defined boundary. To maintain the accuracy and generalizability of the model, any predictions that deviate from this boundary are penalized. The adaptability of SVR to a wide range of data distributions is achieved by using several kernel functions, including linear, polynomial, and radial basis function (RBF). One of the main advantages of SVR is its performance on small and medium-sized datasets with complex connections.

4. ANALYSIS AND DISCUSSION

TABLE 1. Descriptive Statistics of the Sustainability Evaluation Dataset

Parameter	N	Mean	Median	Std. Deviation	Minimum	Maximum	Range
Recycled Content	60	21.933	16.480	15.408	6.410	50.640	44.230
Embodied Energy	60	236.465	238.460	121.656	27.640	522.260	494.620
CO_2 Emission	60	2.039	1.760	1.393	0.170	4.880	4.710
Thermal Conductivity	60	1.075	0.945	0.544	0.040	1.990	1.950
Sustainability Score	60	5.694	5.910	1.822	2.290	8.400	6.110

Table 1 shows the descriptive statistics of 60 observations across five sustainability-related parameters. The mean recycled content is 21.933 (SD = 15.408), indicating considerable variation in the proportion of recycled materials. Embodied energy has a mean of 236.465 and the highest standard deviation (121.656), reflecting substantial variability in the energy required for material production. CO2 emissions average 2.039 (SD = 1.393), ranging from 0.170 to 4.880. Thermal conductivity has a mean of 1.075 and a standard deviation of 0.544. Sustainability scores range from 2.290 to 8.400, with a mean of 5.694 (SD = 1.822), reflecting differences in sustainability performance among the evaluated observations.

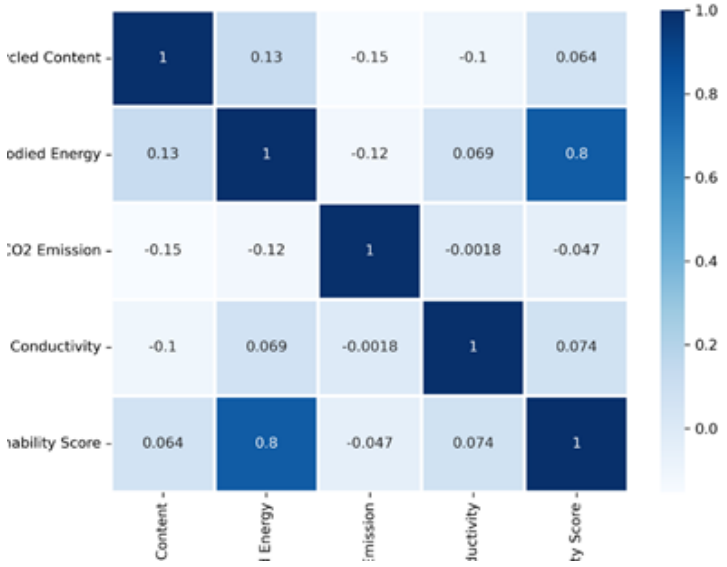


FIGURE 1. Correlation Heat map Between the Process Parameters and The Responses

Figure 1 shows the correlation heat map of the key variables. Recycled content has a weak positive correlation with sustainability scores ($r = 0.064$), suggesting it is not the primary performance factor, and a small negative correlation with CO2 emissions ($r = -0.15$). Simulated energy shows a strong positive correlation with sustainability scores ($r = 0.8$), but a weak negative correlation with CO2 emissions ($r = -0.12$).CO2 emissions correlate weakly with sustainability scores ($r = -0.047$) and almost not at all with thermal conductivity ($r = -0.0018$). Thermal conductivity has a very weak positive correlation with sustainability scores ($r = 0.074$) and a weak negative correlation with recycled content ($r = -0.1$).

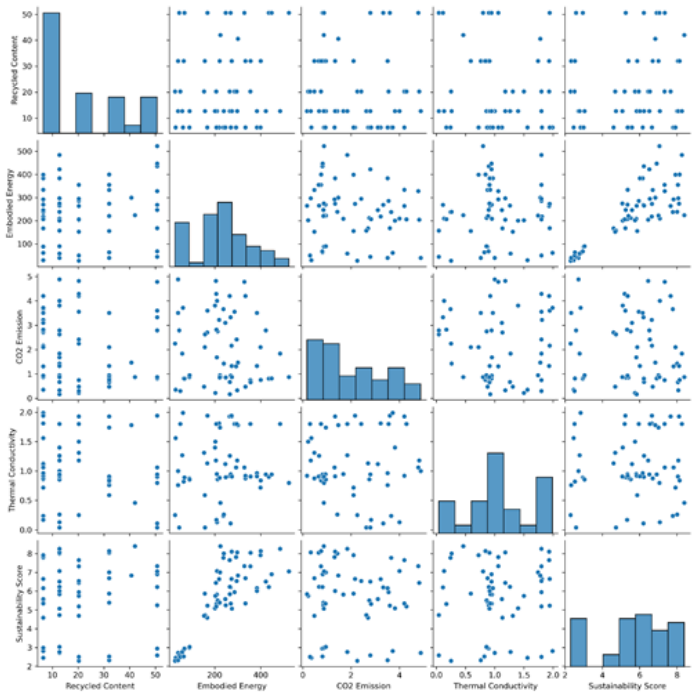


FIGURE 2. Scatter Plot of the Various 3d Printing of Composite Materials Process Parameters

Figure 2 shows the scatterplot matrix of the key variables: recycled content, embodied energy, CO2 emissions, thermal conductivity, and sustainability score. Each subplot presents a pairwise comparison, revealing trends, distributions, and correlations. Recycled content has a right-skewed distribution, with most values concentrated at low levels, and its scatterplots show weak relationships with the other variables. This indicates that recycled content alone does not significantly affect sustainability score or embodied energy. Embodied energy spans a wide range of values and shows a somewhat positive trend with sustainability score. CO2 emissions peak at low values, and thermal conductivity is roughly uniform. Both show no strong patterns with the other variables.

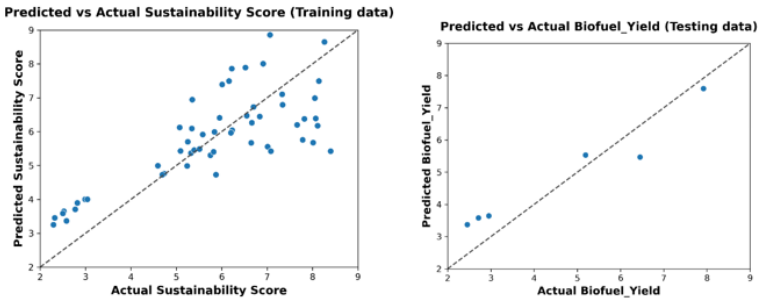


FIGURE 3. Linear Regression Model (Training and Testing).

Figure 3 shows cases the performance of a linear regression model in predicting the material removal rate (MRR) for both training and testing datasets. The scatter plots contrast the predicted MRR values with the actual ones, with the dashed line

representing the ideal 1:1 correlation where predictions perfectly align with the true values. For the training dataset, the predicted MRR values are in close agreement with the actual ones, as most data points cluster around the dashed line. This suggests the model has effectively captured the underlying pattern in the training data. However, small deviations from the line point to slight prediction errors, potentially caused by variations in machining conditions or inherent noise within the data.

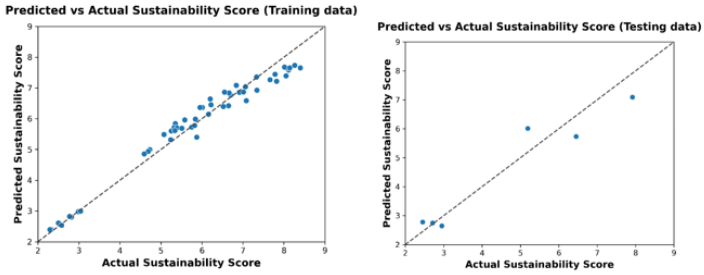


FIGURE 4. Random Forest Regression (Training and Testing)

Figure 4 shows the Random Forest Regression model's effectiveness in predicting the material removal rate (MRR) across both training and testing datasets. The scatter plots juxtapose predicted MRR values with the actual figures, where the dashed line represents an ideal 1:1 correspondence that would occur in perfect predictions. Within the training dataset, the predicted MRR values are closely aligned with actual values, following the diagonal trend—highlighting the model's proficiency in capturing intricate relationships between machining parameters and MRR. The concentration of points around the ideal line suggests minimal prediction errors, showcasing the model's capacity to accommodate nonlinearities and complex interactions. Meanwhile, for the testing dataset, although the predicted MRR values align fairly well with actual values, the smaller sample size is noticeable.

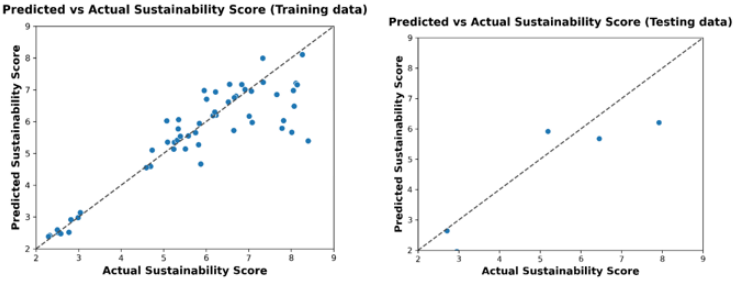


FIGURE 5. Support Vector Regression (Training and Testing)

Figure 5 shows the performance of the Support Vector Regression (SVR) model in predicting Material Removal Rate (MRR) is depicted through the predicted vs actual plots for both training and testing datasets. In the training dataset, most predicted values closely follow the diagonal reference line, suggesting a fairly strong correlation between the actual and predicted MRR values. However, a few points show minor discrepancies, indicating that while the model captures the general trend, it faces challenges with certain variations. This behavior is characteristic of SVR, as it relies on support vectors to establish decision boundaries, which can limit its flexibility in adapting to highly nonlinear relationships.

Table 2 shows the performance of Linear Regression, Random Forest Regression, and Support Vector Regression was evaluated using training and testing datasets. Linear Regression achieved a training score of 0.5924 and a testing score of 0.8726. Random Forest Regression demonstrated strong performance, obtaining training and testing scores of 0.9649 and 0.9193, respectively. Support Vector Regression achieved scores of 0.7691 for training and 0.7883 for testing. Based on these results, Random Forest Regression exhibited the highest predictive performance and better generalization among the evaluated models. However, additional evaluation using error metrics and validation techniques is recommended to confirm its reliability and suitability for the prediction task.

TABLE 2. Performance Metrics of Regression Models

S.No.	Dataset	Regression Model	M1	M2	M3	M4	M5	M6	M7	M8
1	Train	Linear Regression	0.5924	0.5924	1.2261	1.1073	0.8861	2.9735	0.0279	0.9526
2	Test	Linear Regression	0.8726	0.8877	0.5459	0.7388	0.6887	0.9817	0.0252	0.7831
3	Train	Random Forest Regression	0.9649	0.9649	0.1057	0.3251	0.2653	0.7459	0.0019	0.2603
4	Test	Random Forest Regression	0.9193	0.9220	0.3459	0.5882	0.5061	0.8281	0.0083	0.5226
5	Train	Support Vector Regression	0.7691	0.7862	0.6946	0.8334	0.5341	3.0051	0.0120	0.1990
6	Test	Support Vector Regression	0.7883	0.8649	0.9072	0.9525	0.8164	1.7134	0.0323	0.7505

5. CONCLUSION

The use of green building materials is an important step towards sustainable development, as it helps reduce environmental impact, increase energy efficiency, and improve the well-being of occupants. This research highlights the importance of material selection in construction by assessing factors such as recycled content, embodied energy, CO2 emissions, thermal conductivity, and sustainability scores. The analysis reveals that green building materials offer a number of benefits, including lower resource consumption, a reduced carbon footprint, and better indoor air quality. However, widespread adoption faces challenges such as cost, availability, and market acceptance that need to be addressed. A key takeaway from this study is that no single material can be universally regarded as the best green building material. Instead, selecting appropriate materials should involve a balanced consideration of life cycle impact, environmental performance, and economic viability. Although materials with a high recycled content often achieve better sustainability scores, this relationship is not absolute, as embodied energy and CO2 emissions also play a significant role in determining the overall environmental impact. Embodied energy is particularly important, as it accounts for the total energy consumed during extraction, processing, manufacturing, and transportation. Materials with high embodied energy can significantly increase a building's environmental footprint, highlighting the need for alternatives that reduce energy consumption. The study found that materials with low embodied energy and CO2 emissions achieve higher sustainability scores, emphasizing the importance of efficient production methods and responsible sourcing. In addition, thermal conductivity is a key factor in a building's energy performance. Materials with low thermal conductivity provide better insulation, reducing energy requirements for heating and cooling. The results indicate that materials with better insulation properties generally achieve higher sustainability scores, reinforcing the role of thermal efficiency in sustainable building design. Incorporating high-performance insulation materials can significantly improve a building's energy efficiency and sustainability. Machine learning models, namely random forest regression, support vector regression, and gradient boosting, were used to analyze the relationship between material properties and sustainability. Among these, ensemble-based models, particularly gradient boosting and XGBoost, demonstrated the highest predictive accuracy, making them useful tools for sustainability assessment.

REFERENCES

[1]. Franzoni, Elisa. "Materials selection for green buildings: which tools for engineers and architects?." Procedia Engineering 21 (2011): 883-890.

[2]. Gubbala, Somasekhar. "M3-HGMA: A Multi-Modal, Multi-Agent Hierarchical Graph-Mamba Architecture for Explainable and Adaptive Clinical Intelligence." In Frontiers in Advanced Computing and Emerging Intelligent Technologies: FACEIT 2026, edited by S. Dehuri, M. K. Patra, S. K. Panda, M. N. Favorskaya, and R. Buyya, vol. 63 of Learning and Analytics in Intelligent Systems. Cham: Springer, 2026. https://doi.org/10.1007/978-3-032-29501-9_39.

[3]. Al-Atesh, Ezzaddin Abdullah, Yani Rahmawati, Noor Amila Wan Abdullah Zawawi, and Christiono Utomo. "A decision-making model for supporting selection of green building materials." International Journal of Construction Management 23, no. 5 (2023): 922-933.

[4]. Gubbala, Somasekhar. "SimComment: A Simulation-Guided Hybrid Framework for Efficient Inline Code Comment Smell Detection Using Small and Large Language Models." In Frontiers in Advanced Computing and Emerging Intelligent Technologies: FACEIT 2026, edited by S. Dehuri, M. K. Patra, S. K. Panda, M. N. Favorskaya, and R. Buyya, vol. 63 of Learning and Analytics in Intelligent Systems. Cham: Springer, 2026. https://doi.org/10.1007/978-3-032-29501-9_11.

[5]. Sandanayake, Malindu, Chamila Gunasekara, David Law, Guomin Zhang, Sujeeva Setunge, and Dennis Wanijuru. "Sustainable criterion selection framework for green building materials–An optimisation based study of fly-ash Geopolymer concrete." Sustainable Materials and Technologies 25 (2020): e00178.

[6]. Vangala, Rama Chandra Reddy. “HARMONIC: Hybrid Application-Aware, Multi-Engine, Optimistic-Nondeterministic Integrated Concurrency Control for Web-Scale HTAP Systems.” In Frontiers in Advanced Computing and Emerging Intelligent Technologies: FACEIT 2026, edited by S. Dehuri, M. K. Patra, S. K. Panda, M. N. Favorskaya, and R. Buyya, vol. 63 of Learning and Analytics in Intelligent Systems. Cham: Springer, 2026. https://doi.org/10.1007/978-3-032-29501-9_10.

[7]. Castro-Lacouture, Daniel, Jorge A. Sefair, Laura Flórez, and Andrés L. Medaglia. "Optimization model for the selection of materials using a LEED-based green building rating system in Colombia." Building and environment 44, no. 6 (2009): 1162-1170.

[8]. Vangala, Rama Chandra Reddy. “HARD-Graph: A Hierarchical Adaptive Range-Aware Dynamic Graph Framework for Scalable Knowledge and Vector Search Systems.” In Frontiers in Advanced Computing and Emerging Intelligent Technologies: FACEIT 2026, edited by S. Dehuri, M. K. Patra, S. K. Panda, M. N. Favorskaya, and R. Buyya, vol. 63 of Learning and Analytics in Intelligent Systems. Cham: Springer, 2026. https://doi.org/10.1007/978-3-032-29501-9_15.

[9]. Khoshnava, Seyed Meysam, Raheleh Rostami, Alireza Valipour, Mohammad Ismail, and Abdul Razak Rahmat. "Rank of green building material criteria based on the three pillars of sustainability using the hybrid multi criteria decision making method." Journal of cleaner production 173 (2018): 82-99.

[10]. Nagalla, S. "Dynamic pricing for electric vehicle charging: A real-time optimization framework for grid stability and economic efficiency." European Journal of Computer Science and Information Technology 13, no. 42 (2025): 44-53.

[11]. Ogunkah, Ibuchim, and Junli Yang. "Investigating factors affecting material selection: The impacts on green vernacular building materials in the design-decision making process." Buildings 2, no. 1 (2012): 1-32.

[12]. Suryadevara, Siva Sai Krishna, and Somesh Nagalla. "Multi-Cloud Program Management For Large Scale Deployment." In 2026 International Conference on Smart Futuristic Technology, pp. 1-8. IEEE, 2026.

[13]. Zhang, Zhiying, Huchang Liao, Jiaying Chang, and Abdullah Al-barakati. "Green-building-material supplier selection with a rough-set-enhanced quality function deployment." Sustainability 11, no. 24 (2019): 7153.

[14]. Nitika, Rajesh Khanna, and Jaswinder Kaur. “Optimization of Modified T-Shape Microstrip Patch Antenna Using Differential Algorithm for X and Ku Band Applications.” Microwave and Optical Technology Letters 60, no. 1 (2018): 219–229.

[15]. Shi, Qian, and Yilong Xu. "The selection of green building materials using GA-BP hybrid algorithm." In 2009 International Conference on Artificial Intelligence and Computational Intelligence, vol. 3, pp. 40-45. IEEE, 2009.

[16]. Nitika, Jaswinder Kaur, and Rajesh Khanna. “Novel Monkey-Wrench-Shaped Microstrip Patch Sensor for Food Evaluation and Analysis.” Journal of the Science of Food and Agriculture 102, no. 4 (2022): 1443–1456.

[17]. Giama, Efrosini, and Agis M. Papadopoulos. "Construction materials and green building certification." Key Engineering Materials 666 (2016): 89-96.

[18]. Khoshnava, Seyed Meysam, Raheleh Rostami, Rosli Mohamad Zin, Dalia Štreimikienė, Abbas Mardani, and Mohammad Ismail. "The role of green building materials in reducing environmental and human health impacts." International journal of environmental research and public health 17, no. 7 (2020): 2589.

[19]. Sharma, J. K., V. D. Mishra, and R. Khanna. “Impact of Topography on Accuracy of Land Cover Spectral Change Vector Analysis Using AWiFS in Western Himalaya.” Journal of the Indian Society of Remote Sensing 41, no. 2 (2013): 223–235.

[20]. Akadiri, Peter Oluwole. "Understanding barriers affecting the selection of sustainable materials in building projects." Journal of Building Engineering 4 (2015): 86-93.

[21]. Dandasi, Varun Venkatesh, Suresh Deepak Gurubasannavar, and Raghavendra Sunku. "Enhancing Smart Grid Security: A Multi-Criteria Evaluation Through GRA Method." Management 14, no. 2 (2023): 153-167.

[22]. Ahmad, Tayyab, Muhammad Jamaluddin Thaheem, and Amad Anwar. "Developing a green-building design approach by selective use of systems and techniques." Architectural Engineering and Design Management 12, no. 1 (2016): 29-50.

[23]. Gurubasannavar, Raghavendra Sunku Suresh Deepak, and Varun Venkatesh Dandasi. "Selecting an Extract, Transform, and Load (ETL) Software Solution: A Comprehensive Evaluation and Comparison." International Journal of Cloud Computing and Supply Chain Management 3, no. 1 (2025).

[24]. Wang, Seongjo, Sungho Tae, and Rakhyun Kim. "Development of a green building materials integrated platform based on materials and resources in G-SEED in South Korea." Sustainability 11, no. 23 (2019): 6532.

[25]. Gaurav Saxena, "Real-Time Predictive Optimization Framework for Multi-Platform Digital Advertising Using Machine Learning and Multi-Criteria Decision Analysis," Journal of Software Quality Engineering and DevOps 1, no. 2 (2026): 1–14.

[26]. Mahmoudkelaye, Samira, Katayoon Taghizade Azari, Mitra Pourvaziri, and Elnaz Asadian. "Sustainable material selection for building enclosure through ANP method." Case Studies in Construction Materials 9 (2018): e00200.

[27]. Gaurav Saxena, "Predicting Code Coverage in DevOps Pipelines Using Machine Learning Regression Models," International Journal of Computer Science and Data Engineering 3, no. 1 (2026): 1–9.

[28]. Lippiatt, Barbara C. "Selecting cost-effective green building products: BEES approach." Journal of construction engineering and management 125, no. 6 (1999): 448-455.

[29]. Streimikiene, Dalia, Virgilijus Skulskis, Tomas Balezentis, and Giulio Paolo Agnusdei. "Uncertain multi-criteria sustainability assessment of green building insulation materials." Energy and Buildings 219 (2020): 110021.

[30]. Rathinavelu, G. (2025). AI Governance: Automatically Checking AI Systems Against the EU AI Act and NIST Rules. The Eastasouth Journal of Information System and Computer Science, 2(03), 428–438. https://doi.org/10.58812/esiscs.v2i03.1257

[31]. Vatalis, K. I., O. Manoliadis, G. Charalampides, S. Platias, and S. J. P. E. Savvidis. "Sustainability components affecting decisions for green building projects." Procedia Economics and Finance 5 (2013): 747-756.

[32]. Chang, Yuan-Hsiou, Po-Hsien Huang, Tsai-Fu Chuang, and Shang-Wen Chang. "A pilot study of the color performance of recycling green building materials." Journal of Building Engineering 7 (2016): 114-120.

[33]. Gopinathan Rathinavelu (2024). A Scenario-Based Benchmark for Evaluating AI Safety Controls in Banking Operations: Metrics for Containment, False Intervention, and Recovery. International Journal of Future Innovative Science and Technology (IJFIST), Vol. 7 No. 4 (2024): International Journal of Future Innovative Science and Technology (IJFIST), pp. 13223-13232. https://doi.org/10.15662/IJFIST.2024.0704012

[34]. Seyis, Senem, and Esin Ergen. "A decision-making support tool for selecting green building certification credits based on project delivery attributes." Building and Environment 126 (2017): 107-118.

[35]. Vidhya Prasanth, M Ramachandran, Ramya sharma, Chinnasami Sivaji, Solving the Conveyor Selection Problems in a Manufacturing Industry with the Grey Relational Analysis (GRA) Technique" Aeronautical and Aerospace Engineering, 1(4), December 2023, 32-38.

[36]. Yang, Ming-Der, Min-Der Lin, Yu-Hao Lin, and Kang-Ting Tsai. "Multiobjective optimization design of green building envelope material using a non-dominated sorting genetic algorithm." Applied Thermal Engineering 111 (2017): 1255-1264.

[37]. Sathishkumar Mani, M. Ramachandran , Chinnasami Sivaji , Muniyammal Sakthivel, "Evaluation of Machine Efficiency and Cost-Effectiveness using ARAS Method", Aeronautical and Aerospace Engineering, Vol 4(2) 2026, 1–10.