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Original Article

AI-Powered Decision Support for Sustainable Material and Design Selection in Buildings: Reducing Cost and Carbon Impact

Tara R. AbdulWahab

University of Al-Hamdaniya, Nineveh, Iraq.

Corresponding Author : tara.raad@uohamdaniya.edu.iq

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Abstract *- Artificial intelligence has become the key to speed, growth, and development. It has created a broad scope for development, so it is necessary to rely on it to achieve the sustainability that countries and people have always sought. Since the construction sector is one of the leading sectors in the field of heat emissions, especially in terms of energy consumption for adaptation, we sought through this research to work on creating an Artificial Intelligence-based decision-making system for selecting sustainable materials and design in order to achieve two goals: cost-efficiency and sustainability. A comparison was made between three types of materials: regular bricks, hollow blocks, and thermostone. Standards were set to achieve both goals together through this system, and thermostone achieved the most sustainability, while hollow blocks were the most economical.*

Keywords **-** *Carbon footprint, Cost, AI, Decision support, Sustainable.*

1. Introduction

The construction and residential sectors are among the most energy-intensive, with air conditioning (both cooling and heating) being the most expensive energy-consuming activity. Therefore, sustainability is crucial for reducing this consumption and increasing the sector's efficiency and effectiveness in terms of energy savings and carbon footprint. One of the determining factors in energy saving and reducing the amount of carbon dioxide emissions is the materials used in the structure of buildings. In recent years, manufacturing companies and businesses have tried to produce and use different materials, targeting the smallest carbon footprints. The results have been numerous diverse materials with different carbon footprints for the construction companies to use in buildings.

Another key element to be taken into consideration by building companies is sustainability, which is maintaining a balance between using the most appropriate materials for the current needs and, at the same time, preserving them for the following generations. The appropriacy of materials is defined in terms of factors like efficiency, cost, and carbon dioxide emissions. In choosing construction materials, it is of utmost importance to consider insulation and economic efficiency. However, the decision-making systems, along with Artificial Intelligence, have made the selection of materials more efficient as they offer a substantial database that details the efficacy of various building and construction materials. Furthermore, AI has enabled the integration of two important criteria: reducing carbon footprint and minimizing costs. These two criteria represent the fundamental factors in selecting building materials, in addition to feasibility and other considerations. Therefore, the lack of integration between reducing the carbon footprint and lowering costs through decisions aimed at sustainability does not provide a comprehensive solution. This is the research problem we seek to address. One of the main objectives of this research is to propose a model for comparing two criteria: the first is the carbon footprint, and the second is cost. These two criteria form the basis for selecting the materials required for the construction projects to be carried out.

2. Literature Review

Buildings consume most of the energy in air conditioning operations, and the process of selecting building materials is essential to achieving sustainability for buildings, as these building materials can enhance environmental, economic, and social benefits. To select these materials, we must evaluate the environmental benefits, as sustainable materials have a remarkable ability to reduce emissions and the carbon footprint, in addition to saving energy consumption [1, 2]. Sustainable materials have a higher initial cost than their counterparts, but in the long run, this cost is reduced through maintenance and operation [1].

In addition, these materials can improve indoor air quality and raise the level of health [3]. In addition, government legislation and regulatory frameworks must be strengthened to promote sustainability and its practices. The life cycle assessment method involves evaluating the environmental impact of building materials [4]. Through green developments, building modeling methods have been relied upon to improve accuracy and efficiency [5]. However, the remaining challenges were through the environmental interoperability of this software and the standardization of the standards on which they would be based [6]. The use of green materials has had a role and impact on the building life cycle. Despite these developments, there is still a need for research to address data quality issues [3].

Recent research has focused on the role of computer software in assisting the design process and improving the selection of materials for sustainable construction. It can integrate Life Cycle Assessment (LCA) processes, which reduce environmental impact [7]. In addition, there are multiple decision support systems that rely on several ambiguous methods in the process of selecting materials, but they take into account environmental and social aspects [8]. This method is commonly used, especially at the beginning of the design process [9]. These tools can highlight sustainable materials for designers and compare them [10].

Artificial intelligence algorithms are increasingly being applied, particularly in improving decision-making in information systems, where they improve the processing of complex data collected from various sources [11]. We can say that machine learning algorithms have played a role in the development of science [12], and their tools have played a role in decision-making [13]. Artificial intelligence has revolutionized the provision of accurate information [14]. The process of predicting materials created by artificial intelligence tools, especially those related to the process of selecting sustainable materials that can be used in construction [15], can be cited as an example of the use of Artificial Intelligence in material selection, where the compressive strength of concrete cast samples can be predicted, as this process can improve testing costs [16].

There are several platforms, such as SMARTMIX, which focus on concrete mixtures and seek to improve them [17]. In addition, there are Neural Networks, which are accurate based on the results they have obtained [18]. Artificial Intelligence has also enabled decision support systems to analyze materials regarding carbon footprints in order to come up with the most efficient one for construction [19], which can, in turn, save time and cost, along with maintaining sustainability [20]. The role of AI in construction material selection goes even further by being able to manage risk factors effectively [21]. By considering cost, stakeholders can use AI to make sure their construction goals are achieved [22]. Even with all of this advancement in AI, more work needs to be done before it can be widely used. The integration of BIM technologies can play a role in furthering this development and thus achieving sustainable development goals [23]. Comparing our research with the reference studies reviewed, we can say that it differs from previous studies in that its focus is on reducing both the carbon footprint and the cost simultaneously. While the reference studies addressed the importance of sustainable materials and focused on improving energy efficiency and the carbon footprint without considering the integration of cost and carbon footprint, our research aims for multi-objective improvement. It provides an explanatory framework that facilitates designers' understanding and decision-making.

3. Research Gap

Most of the research we were able to see focuses on only one factor, either cost or pollution reduction, each criterion separately. However, realistic projects require a process of balancing economic improvement and environmental sustainability, as these systems rely on numerous databases of traditional materials, where innovative alternatives are rarely included. Moreover, Artificial Intelligence systems cannot add factors such as geographical location, local regulations, and others. These systems may be suitable in theory, but are not practical to implement. These gaps must be addressed to arrive at systems that have the ability to improve cost and sustainability simultaneously.

4. Aim of this Research

Develop a simple AI-based model that helps in choosing construction materials and designs with the lowest cost and lowest carbon emissions.

5. Data Collection

By relying on data from the Central Statistical Organization in Iraq and available reference studies, the author collects information on the carbon footprint and the price of materials in order to evaluate both together, as outlined in Table 1. To simplify the procedure, the cost and carbon footprint of a square meter of wall for three materials have been calculated: regular brick, large block, and thermostone. The results are presented in Table 2.

Data were compiled from primary sources: the Iraqi Statistical Publications 2025, carbon footprint data from environmental producer permits, and global studies. Significant problems were identified, including data assimilation issues and discrepancies between cost and footprint ranges. Several novel techniques were previously applied: first, converting all data to length and carbon footprint for the wall, using length conversion agreements for each material. Second, normalizing the data using Min-Max

Scaling to minimize values between zero and one, with zero being the optimal value for each criterion. Third, establishing long-distance trend lines between corresponding cost and corresponding carbon footprint. Finally, considering geographical variations, the analysis took into account the diversity of factors (economic, optional, or balanced).

Table 1. Material cost and carbon footprint

Material	Number of Units	Price	Carbon Footprint Index (GWP, KgCO2e)	Reference
Regular brick	1000	160	0.55	[24, 25]
Republican brick	1000	205	0.55	[25, 26]
Medium hollow concrete block	1000	546	1.4	[25, 26]
Large hollow concrete block	1000	640	1.8	[25, 26]
Thermostone	1000	1850	3.9	[25, 27]
Ordinary cement	1ton	115	732	[25, 28]

Table 2. Material cost and carbon footprint for 1m^2

System	No. Units	Price	Carbon Footprint
Clay Bricks	120	26,115	100.6
Hollow Concrete Block	12.5	11,327	99.8
Thermostone	6.67	18,093	32.6

6. Building a Decision Support System

The key to our research is achieving a balance between cost and sustainability. Cost was determined by price, while sustainability was determined by the carbon footprint criterion to strike a balance between these two criteria and achieve the following goal:

1. Reducing the cost per square meter.
2. Reducing the carbon footprint and, consequently, carbon emissions.

We have applied the following standards in order to ensure that we achieve the goal we seek:

$$\frac{E_i - \mathrm{Min}(E)}{Max(E) - \mathrm{Min}(E)} = E_{norm}$$

$$\frac{C_i - Min(i)}{Max(C) - Min(c)} = C_{norm}$$

Where, C_i : $Cost\ per\ m2, E_i$: $embodied\ carbon\ (Kg\ Co_2/m^2)$

The Composite Decision Score is the sum of the two numbers obtained from the cost and the Carbon Footprint.

$$C_{norm} * w_E + E_{norm} * w_c = Score\ (i)$$

: w_E, w_C: These are weights that are taken according to the greater importance. If carbon is more important to us, we give it a greater value, and if cost is more important, we give it a greater number, but their sum must always be one. 0.5 / 0.5 Balance, 0.8 / 0.2 Preferred for sustainability, 0.2 / 0.8 Preferred for economic. As shown in Table 3.

In this research, we trained a decision tree classifier using the cost of one square meter of space as input parameters. The model achieved 100% accuracy in the test partitioning. The extracted rules were highly interpretable. When cost was the primary consideration, we selected hollow concrete blocks.

Otherwise, thermostone was the most sustainable and efficient. The model did not select clay bricks in any scenario due to their high cost and carbon footprint, as outlined in Figure 1.

The decision tree model implemented in this study achieved perfect classification accuracy (100%) when evaluated on the dataset used. It is worth noting that this high accuracy primarily reflects the limited nature of the exploratory dataset (three building materials after transformation) and the deliberate simplicity of the illustrative model.

To ensure the reliability of the results, several measures were taken to minimize the risk of overfitting, including limiting the tree depth and ensuring that the extracted decision rules were simple, interpretable, and consistent with geometric logic. However, it is crucial to emphasize that this accuracy represents the model's performance on its training data within this narrow context.

In large-scale practical applications, where the data is more complex and diverse, this percentage is expected to decrease. Therefore, the study recommends that future research incorporate robust validation techniques such as cross-validation and utilize larger datasets to test the model's robustness and generalizability before its adoption in supporting real-world design decisions.

Table 3. Rank of materials

		Cost	Carbon Footprint	Cost norm	Carbon norm	Score	Rank
Balance	**Thermostone**	18093	32.6	0.458	0	0.229	1
Balance	**Hollow bricks**	11327	99.8	0	0.988	0.494	2
Balance	**Clay bricks**	26115	100.6	1	1	1	3
Economic	**Hollow Bricks**	11327	99.8	0	0.988	0.198	1
Economic	**Thermostone**	18093	32.6	0.458	0	0.366	2
Economic	**Clay bricks**	26115	100.6	1	1	1	3
Sustainability	**Thermostone**	18093	32.6	0.458	0	0.092	1
Sustainability	**Clay bricks**	26115	100.6	1	1	1	3
Sustainability	**Hollow Bricks**	11327	99.8	0	0.988	0.791	2

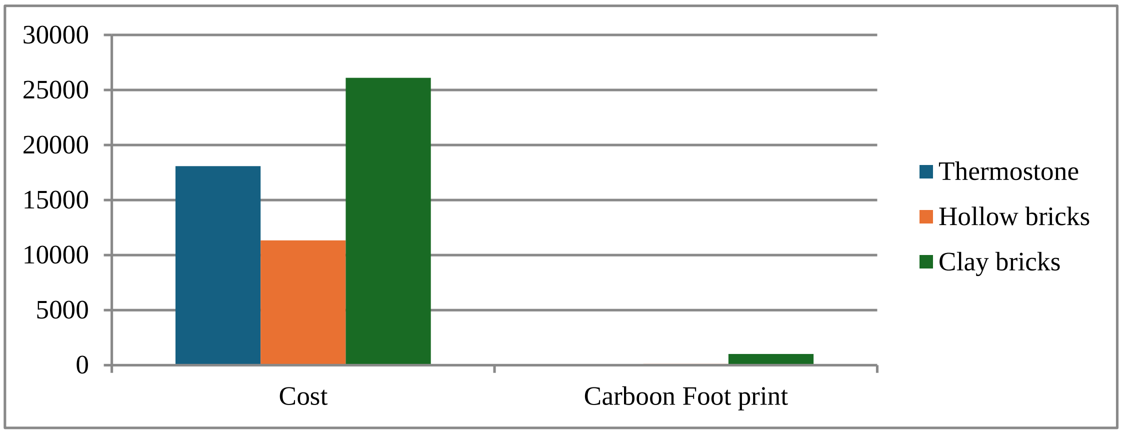

Fig. 1 Cost and carbon footprint

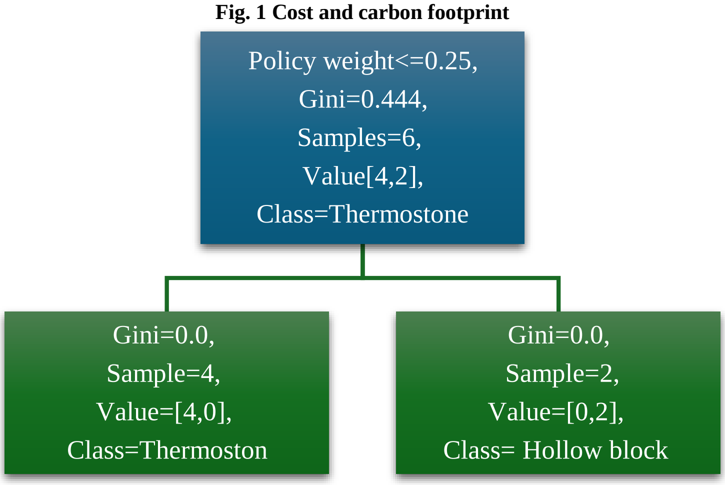

Fig. 2 Change the resolution between hollow block and thermostone

7. Results and Decision

The results of the multi-criteria decision-making analysis indicated that among the three wall systems, cellular bricks consistently achieved the lowest embodied carbon emissions at a moderate cost. In contrast, cellular bricks showed the highest cost and highest carbon footprint, while hollow bricks emerged as the least expensive option, with carbon emissions almost identical to those of bricks. In the equal weight distribution scenario, cellular bricks were ranked as the most suitable system, while when economics were required, hollow bricks were preferred, and thermoset concrete was the priority in the environmental objectives scenario. Because the decision criteria depended on a decision tree that incorporated cost, carbon, and the policy preference index, they were relatively simple to comprehend. When it comes to economics, hollow bricks were preferred, while considering sustainability, cellular bricks were the best choice. The results of comparing the model based on Artificial Intelligence with the computed results showed that application of AI, along with the strategies to maintain sustainability, can achieve a balance where the importance of economic viability is parallel to carbon reduction aims.

8. Case Study

In this study, a case study has been used by the author in order to analyze and compare 2 designs for a small 2-floor building. In the supposed building, the current conventional materials, including regular glass, steel, and concrete, were compared to materials that were selected by AI and were supposed to be sustainable.

The price of the materials was estimated by the author using the data from the market and the studies that were conducted previously. Having taken into account the amount of materials required for the building, the author presented 2 solutions. In the first solution, the current conventional materials are used. In contrast, in the second solution, the materials were selected by the AI for being sustainable and low in carbon footprint. We may examine the quantities required in each of the two scenarios, their costs, and carbon footprints using Table 4.

For the comparison study, Table 5 displays each material's total cost and total footprint. According to Table 6 and Figure 3, utilizing sustainable materials would result in a $7,959 increase in building costs above standard materials. It can be observed that the carbon footprint has significantly decreased to one-third. One matter that needs to be considered is the time duration needed for the extra cost to be recovered by saving energy. It is estimated that the additional cost can be recovered in 6 to 10 years' time.

Table 4. Quantities of materials for both cases

Item	Unit	Quantity	Baseline: Unit Cost	Baseline: Unit Carbon (kgCO2e/unit)	Sustainable: Unit Cost	Sustainable: Unit Carbon (kgCO2e/unit)
Structural concrete (m3)	m3	31.2	110	300	125	180
Rebar steel (t)	t	3.12	900	1800	950	800
External Glazing (m2)	m2	55.77096	120	120	160	100
External solid wall (m2)	m2	130.1322	45	120	55	70
Roof insulation (m2)	m2	60	0	0	20	10
Wall insulation (m2)	m2	130.1322	0	0	20	10

Table 5. All quantities of materials for both cases

Item	Unit	Quantity	Baseline: Unit Cost	Baseline: Unit Carbon (kgCO2e/unit)	Sustainable: Unit Cost	Sustainable: Unit Carbon (kgCO2e/unit)	Baseline: Cost	Baseline: Carbon (kgCO2e)	Sustainable: Cost	Sustainable: Carbon (kgCO2e)
Structural Concrete (m3)	m3	31.2	110	300	125	180	3432	9360	3900	5616
Rebar Steel (t)	t	3.12	900	1800	950	800	2808	5616	2964	2496
External Glazing (m2)	m2	55.77096	120	120	160	100	6692.515	6692.515	8923.354	5577.096
External Solid Wall (m2)	m2	130.1322	45	120	55	70	5855.951	15615.87	7157.273	9109.257
Roof Insulation (m2)	m2	60	0	0	20	10	0	0	1200	600
Wall Insulation (m2)	m2	130.1322	0	0	20	10	0	0	2602.645	1301.322

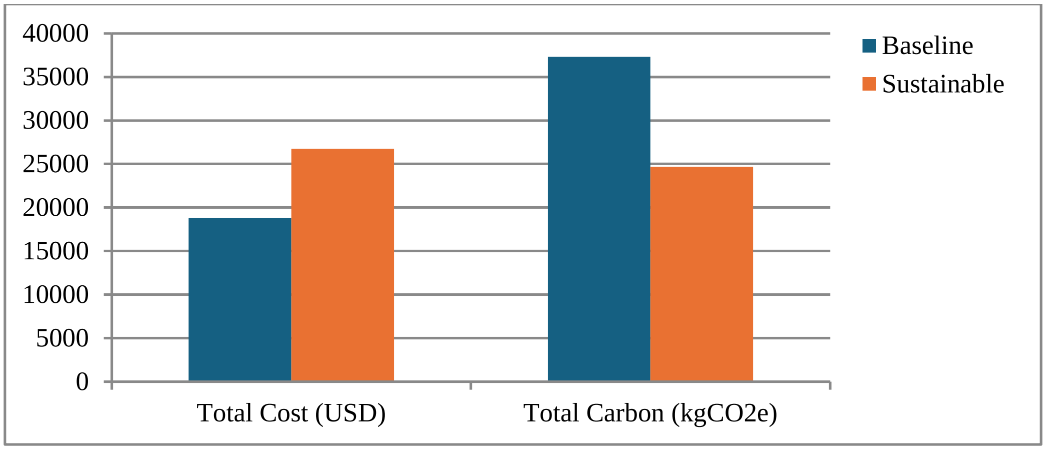

Fig. 3 Total cost & carbon print

Table 6. Total cost and carbon

Scenario	Total Cost (USD)	Total carbon ($kgCO_2e$)
Baseline	18788.47	37284.38
Sustainable	26747.27	24699.68

9. Conclusion

This study showed the significance of Artificial Intelligence in choosing the appropriate materials that can result in more sustainable designs. A multi-criteria decision-making analysis has been applied in this study. Using this model, the author was able to compare several building material options based on two criteria: cost and sustainability. This study concluded with a comparison of several materials, a new method that can be built upon in advanced research to develop more comprehensive models.

In addition, the author compared two-story buildings in terms of the cost and carbon footprint differences between using traditional materials in the construction process and using sustainable materials selected by Artificial Intelligence.

We found a cost difference between the two. This difference is expected to be recovered within the first ten years due to the ever-increasing energy costs. Through our model, we can say that it represents the beginning of this rapidly evolving approach and a form of harnessing technology in the service of humanity.

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