Intellectual Tool to Compute Embodied Energy and Carbon Dioxide Emission for Building Construction Materials

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Abstract. Every material has its capacity to consume energy called embodied energy (EE) and to emit CO₂ during the manufacturing process. The estimation procedure of EE and CO₂ emission is predominantly based on the existing case examples from various nations across the globe. There is an impressive aperture in instances from developing nations concerning an appraisal of embodied energy and emission of CO₂ for used building construction materials. The available tools are also not much user friendly and hence not everyone is capable to use it easily. From this point of view, this research aims to develop an intellectual tool to find out embodied energy and CO₂ emission for building materials. This research presents a model for estimation of EE and emission of CO₂ (E4-Model) for various building materials used in construction. This research focuses on construction of building in the Indian Construction Section. For the assessment of EE and CO₂ emission, the concept of Convolutional Neural Network (CNN) is used and all the values are by weight of material. From the experimental analysis, it is observed that the estimation accuracy of the system is more than 99.62% for small as well as large buildings. The research concluded that the use of CNN is far better than the artificial neural networks in terms of system response time and complexity to estimate the EE and CO₂ emission rates. In the research proposed E4-Model is applied and developed using the concept of deep learning and curve-fitting toolboxes within MATLAB Software. The actual emission for all the tested projects were found to be lesser than the estimated emission. The tool developed using CNN proved to work with high accuracy.

Keywords: Residential Building, Construction Material, Embodied Energy, Embodied Carbon (CO₂), Convolutional Neural Network

1. Introduction

Total global energy consumed by the construction industry is more than 40% and it is responsible for 25% of embodied carbon (CO₂) emissions [1]. Raw materials used by the construction industry are more than any other industrial sector and considered a major source to generate a large amount of embodied energy and carbon [2]. The amount of used material by this industry is more than half of total materials excavated/devised from the crust of Earth [3]. To construct a building a large number of raw materials are used and for their production energy is consumed and CO₂ emission occurs. So buildings and construction industries are liable for a little over 40% global energy consumption with a high rate of CO₂ emissions and it is reported by the United Nations Environment Program (UNEP) [4]. Such a colossal weight on the earth adds to negative results and from this segment, the demand for global energy will rise due to:
Energy access improved due to development.
Generous utilization of energy-consuming gadgets.
The exponential development of the construction sector.

The resource and emission cycle of EE and Carbon Dioxide (CO2) of buildings and construction sector is shown in figure 1.

Figure 1. EE and CO2 Emission Process

The above figure illustrates the process of EE and carbon Dioxide (CO2) emission of any general structure in the construction industry. The basic meaning and description of EE and CO2 emission can be written as:

Embodied Energy: It defines the energy which is consumed by every procedure involved in the generation of any structure, right from the extraction and sorting of characteristic assets up till congregation, transfer and item conveyance [5]. Embodied energy excludes the activity and transportation of the structured material, which is considered in a real existence cycle approach anyways [6]. Embodied energy is essentially the 'intricate' or 'mainframe' segment for the existence cycle effect of any particular home. The chain of embodied energy for building erection is explained in figure 2.

Figure 2. Chain of EE in Construction Industry

From the above figure 2, we concluded that every used material having its rate of embodied energy generation which is enlisted in table 1. Typical values for some Indian construction materials are given in table 1, which is generally used in the Indian construction industry [7].
CO2 emissions in construction: Since the construction industry plays a huge role in producing gases that contribute to global warming, there is a potential for the industry to dramatically reduce carbon emissions [8]. The CO2 emission from most of the construction industry can be classified in two types:

- The carbon compound generated by the raw building material inclusion of carbon dioxide.
- The carbon released when combustion of fossil fuels occurs.

The construction industry releases carbon in both direct and indirect ways. To estimate the carbon released by the unprocessed material and the construction material, there are 2 primary aspects to measure carbon emission.

| S.No. | Used Materials                        | Embodied Energy - MJ/Kg | Used Materials                        | Embodied Energy - MJ/Kg |
|-------|--------------------------------------|-------------------------|--------------------------------------|-------------------------|
| 1     | General Aggregate                    | 0.083                   | Primary Brass                        | 80                      |
| 2     | General Aluminum                     | 155                     | Secondary Brass                      | 20                      |
| 3     | Cast Products                        | 159                     | General Carpet                       | 74                      |
| 4     | Extruded                             | 154                     | Felt (Hair and Jute) Underlay        | 19                      |
| 5     | Rolled                               | 155                     | Nylon (Polyamide), pile weight 500 g/m² | 180             |
| 6     | Asphalt, 4% (bitumen) binder content (by mass) | 2.86           | Nylon (Polyamide), pile weight 700 g/m² | 230             |
| 7     | General Bitumen                      | 51                      | Nylon (Polyamide) carpet tiles of 700 g/m² in weight | 279             |
| 8     | General Brass                        | 44                      | Nylon (Polyamide) carpet tiles of 900 g/m² in weight | 328             |
| 9     | Nylon (Polyamide) carpet tiles, pile weight 1100 g/m² | 378           | Fiber Cement Panels Uncoated         | 10.4                    |
| 10    | Polyehtylterephalate                 | 106                     | Fiber Cement Panels - (Colour) Coated | 15.3                    |
| 11    | Polypropylene                        | 95.4                    | Mortar (1 : 3 mix for cement and sand) | 1.33                    |
| 12    | Ployurethane                         | 72                      | Mortar (1 : 4)                       | 1.11                    |
| 13    | Rubber                               | 90                      | Mortar (1 : 5)                       | 0.97                    |
| 14    | 16/20 Mpa                            | 0.7                     | Mineral wool                         | 16.6                    |
| 15    | 20/25 Mpa                            | 0.74                    | Paper wool                           | 20.2                    |
| 16    | 25/30 Mpa                            | 0.78                    | Rockwool                            | 16.8                    |
| 17    | 28/35 Mpa                            | 0.82                    | Wood wool (loose)                    | 10.8                    |
| 18    | 32/40 Mpa                            | 0.88                    | Wood wool (Board)                    | 20                      |
| 19    | 40/50 Mpa                            | 1                      | Recycled Wool                        | 20.9                    |

Inspiration & Contributions: The selection of energy-efficient construction materials these days positively affects global warming [9]. Estimation of the EE of used construction materials is major underlying strides which contribute to ecological defending [10]. Various investigations took place to assess the typical energy and its related CO2 emanations of buildings, which are principally founded on contextual investigations from developed nations.
Due to the exponential growth in the building and construction sector, urban as well as rural populations rapidly increasing, especially in developing countries like India. It is likely to cause the EE and CO₂ emissions to upturn further in the future. Survey and analysis by UNEP, more than 230 billion square meters of recent construction has been done in the world and more of it is expected to construct in the next upcoming 40 years [11]. So, to get a better life, the reduction of EE and carbon emission is a major concern. This research represents an intellectual tool to calculate EE and CO₂ emission for construction materials. To summarize, the objectives of the work is:

- To develop an interactive model using the Graphical User Interface (GUI) in Matlab Software with the help of a curve fitting toolbox.
- To train the model for estimation of embodied energy and emission of CO₂ (E4-Model), CNN as a classifier is applied which produces better estimation accuracy and reduces human effort.
- At the end of E4-Model, a comparative analysis is done to verify the performance of the project which is built using Artificial Neural Network (ANN) in our existing work [12].

The rest of the research estimate EE and CO₂ emission for construction materials is organized as follows. The existing related work and their short survey are explained in section 2 and section 3 sum up the implemented methodology for the E4-Model and Section 4 of the research article provides the used dataset description of the evaluation of E4-Model with a relevant comparison of the proposed methodology. Conclusion referring to future possibilities are given in section 5 for estimate embodied energy and CO₂ emission for building materials.

2. Literature survey

This segment discusses the literature of available research based on the estimation of EE and CO₂ emission for building construction materials using different approaches and methods. In Ethiopia, a model for EE and CO₂ emissions of general building construction materials are designed by a group of researchers in 2019 [1]. In this exploration, creators have recognized five generally utilized construction materials. The materials considered in this exploration are sand, aggregate, HCBs, cement, and rebar. The devoured and squandered amounts of given materials and their epitomized vitality and CO₂ outflows inside the lifecycle limit of "support to site" were investigated by analyzing five multi-story commercial and open structures. The assessment of the outcomes showed that concrete, HCBs, and rebar are significant to vitality and also the major contributors for CO₂ emission. Although these three materials represented minimal part of the general weight, the discoveries of this investigation affirmed that they are the prime factors for vitality and the greatest reasons behind CO₂ outflows. Raja Shahmir Nizam in 2018 [2] designed a model for a BIM-rooted tool to estimate EE for structure. The aforementioned work presents a systematic structure to calculate the EE trapped inside the indigenous BIM environment. The application of this structure system is explained by the creation of a tool to calculate the EE of materials, energy used in transportation and construction. To check the applicability of the framework the researcher tested a working version of the tool on a specific project. In this manner both the tool and outcomes verified by specific project and manual calculations respectively.

This research helps to generate an automated process to calculate EE of every material during all the stages of building life cycle including design and development phases. The process segregates the EE in namely three parts: material embodied energy, energy consumed to transport, and consumed energy to construct it. It further investigates the EE for each classified part by employing an amount of materials inputs from BIM authoring tool and pre-assigned databases fed with transportation and construction information. An input-output based hybrid method was developed by two researchers in 2018 [3] where the author experimented on universities and colleges to analysis the EE framework. In this examination work, they urbanized an IO-based mixture (IOH) exemplified energy computation model by incorporating real energy use information into the most recent IO accounts. They coordinated the energy encapsulated in human work and capital sources of info. Besides, the authors also differentiated aggregated construction costs from energy intensity. The research also illustrated the difference between disaggregated costs and also the energy intensities related to cost component-specific to find
out the EE of the building under consideration for the sample. F. N. Rasmussen et al. in 2018 [4] presented an analytical model for calculations of EE and greenhouse gas (GHG) CO2 emissions from buildings. In this research, the author has audited the strategies for exertion estimation to distinguish and survey the scope of epitomized carbon outflows in private structures, by investigating and normalizing issues of vulnerability and equivalence between contextual analyses. After-effects of planned model for exemplified carbon outflows of private structures differ from 179.3 kgCO2e/m²-1050 kgCO2e/m²and for the working stage between 156 kgCO2e/m²-4049.9 kgCO2e/m². The range for encapsulated outflows implants the particular scopes of past overviews yet with numerical contrasts that most likely get from the variety in the framework limits or even from the structure's general plan. Abhilash Mukherjee et al. in 2019 [12], designed a model with the concept of Artificial Neural Network (ANN) to calculate the embodied energy of structures in India. In his research article, the research dealt with the artificial intelligence technique to reduce human effort and achieved better performance for the EE for the frequently used building materials in the Indian construction industry. From the above-mentioned research, we concluded, that the approach is workable with some changes in approach. A detailed database of embodied energy has been referred as base [13].

Based on existing research pieces of literature in the estimation of embodied energy and CO2 emission, it boils down to essential key points that aid in sorting out the problem faced in past for embodied energy estimation models. The main concern in this type of model is to reduce human effort and estimation accuracy to improve the quality of E4-Model. Therefore, it is concluded that CNN is a better choice for model development.

3. Proposed Methodology

The proposed intellectual tool to estimate EE and CO2 emission for building construction materials consists of the five most important steps which are shown in figure 3. This research aims to calculate the EE and CO2 emission for a building before construction based on used materials. The subsequent steps of the proposed model mark the various steps that should be well-grounded:

![Figure 3. Steps of Proposed E4-Model Model](image)

**Step 1:** Design of a simulator to execute the intellectual tool to estimate EE and CO2 emission for building materials which are known as E4-Model. To plan the desired estimation framework, we chose the Graphical User Interface (GUI) of MATLAB Software which provides the appropriate estimation with a random untrained situation. The designed model is shown in figure 4 which is based on CNN as a classifier. To train our proposed model for embodied energy estimation, we create the use of predefined embodied energy generation capacity (Table 1) for different materials which helps to reduce the human effort and give an absolute estimated result for both embodied energy as well as CO2 emission. Such value calculations are considerably easier with the help of an artificial intelligence approach.

**Step 2:** After that, we create the next page of proposed E4-Model which is used for the new entry for building embodied energy and CO2 emission estimation. The designed page for new inputs is shown in figure 5 which contains the welcome window of the proposed E4-Model.
Figure 4. Embodied Energy & CO₂ Estimation Tool

The button named new is there to create a fresh construction work plan. The button called open is for opening any work previously archived. The icon named library is there for reference while providing inputs and it also is the basic source for the execution of the program. The button named sample is there to help the user in providing inputs. The buttons named exit and help are there to provide exiting function from the program and get help about using the tools respectively. The registration page of the proposed E₄-Model is shown in figure 6.

Figure 5. Estimation Tool with New Entry for Estimation
Figure 6. Registration Page of E4-Model

Step 3: To design a page for registration for any project. The above figure represents the registration page of proposed E4-Model which is used for new building registration by providing appropriate details of the project and its details. After fill-up each blank space, we can proceed for the next step by pressing the “Proceed” button, which opens the new page for the “Add Assembly” shown in figure 7.

Figure 7. Add Assembly Page of E4-Model

Step 4: After the registration, the Add Assembly page is designed for proposed E4-Model which is used to add different portions of the building which is constructed and needs to calculate the embodied energy and CO2 emission. Each assembly of this page considers the total used construction materials for a particular section of the building.
**Step 5:** At the last of the model, we calculate the actual embodied energy and CO₂ released into the atmosphere manually and then to estimate the output of manual calculation we use the concept of CNN. CNN description is based on three layers namely Convolutional Layer, Pooling Layer and Output Layer. All three layers are narrated below:

Convolution Layers: Being the basic first layer with fundamental elements that provide input data to chain the E4-Model. This layer examines the suitable and comical properties sets by using a set of learnable square filters. Every filter enforced to the manually calculated values to the proposed model to define CO₂ emission and embodied energy.

Max-pooling Layer: In E4-Model, the next layer which portrays unique properties extraction perspectives by sub-sampling layers. These layers act as an optimum estimation approach to multiply the synthesis for estimation accuracy. The result obtained by this layer is transferred to the next model layer which used for the utmost activation value while creating a structure for the model which returns by the output layer.

Output Layer: this layer is there to give back a trained structure using CNN which is later utilized in the evaluation stage of E4-Model. A typical CNN model is displayed in figure 8.

For every iteration, the actual and manually calculated data is uploaded and then carried to the next layer which is intermediate layer like convolutional layer and the weight of the data is tweaked as per the requirement, and then these values are passed to the output layer, where we get two number of output each resulting from different building attributes. For this purpose, CNN is a better option as compared to the ANN. Figure 9 a shows the cross-entropy, Figure 9 b training state and Figure 9 c shows the error histogram.
The performance of used CNN for E4-Model is evaluated on the ground of the following parameters.

**Table 2.** Parameters used to evaluate performance of CNN

| Parameters used to evaluate performance of CNN | Cross-Entropy | Gradient | Validation |
|-----------------------------------------------|----------------|----------|------------|

![Image](image1)

![Image](image2)

![Image](image3)

**Figure 9.** (a) Cross-Entropy, (b) Training State and (c) Error Histogram
4. Result and Discussion

Here in this part, the executed program of proposed E4-Model are explained with five different building samples to estimate the embodied energy and CO₂ emission and in last we compare with our previous model using the concept of ANN. We consider the equal area for all projects and are is 3×105 m².

Table 3. Result based on Embodied Energy

| S.No. | Project No. | Actual EE (GJ/m²) | Estimated EE (GJ/m²) |
|-------|-------------|-------------------|----------------------|
| 1     | Project 1   | 8.78              | 8.43                 |
| 2     | Project 2   | 8.34              | 8.22                 |
| 3     | Project 3   | 7.57              | 7.34                 |
| 4     | Project 4   | 5.77              | 5.56                 |
| 5     | Project 5   | 4.76              | 4.67                 |

Figure 10. Results based on Embodied Energy

Figure 10 represents the calculated embodied energy for five different projects named as Project 1, 2, 3, 4, 5. From the analysis, we observed that the using of CNN estimates the embodied energy accurately and it is just near to actual embodied energy. In the proposed E4-Model, system accuracy is also better as compared to the model with ANN and estimation of CO2 emission is also accurate.

Table 4. Result based on CO₂ Emission

| S.No. | Project No. | Actual CO₂ Emission (Ton) | Estimated CO₂ Emission (Ton) |
|-------|-------------|---------------------------|------------------------------|
| 1     | Project 1   | 0.831                     | 0.842                        |
| 2     | Project 2   | 0.853                     | 0.858                        |
| 3     | Project 3   | 0.933                     | 0.956                        |
| 4     | Project 4   | 0.984                     | 0.986                        |
| 5     | Project 5   | 0.914                     | 0.943                        |
Figure 11 represents the emitted CO₂ by used materials in building for five different projects similar to the above case. From the analysis, we observed that the use of CNN is estimated CO₂ is exact near to the actual value of CO₂ emission.

![Figure 11. Result based on CO₂ Emission](image)

Figure 12 represents the comparison of the proposed model with our existing model (12) for embodied energy estimation based on their accuracy. In the proposed E4-Model, system accuracy is also better as compared to the model with ANN and estimation of CO₂ emission is also accurate. So we concluded that the use of deep learning in the construction field is also a beneficial and effortless process.

![Figure 12. Comparison of Results](image)
5. Conclusion
In the attempt to calculate EE of any building an ANN-based tool is required to acquaint which is called the E4-Model. It gives a in-depth analysis of applicability and possible challenges in estimating embodied energy which is believed to be a rather complicated task in the construction industry. The embodied energy and CO2 emission are calculated with more accuracy. In addition to this, this model estimates the EE on the substratum of EE for the used building construction material by weights. From the experimental result analysis, it is observed that the estimation accuracy of the system is more than 99.62% for small as well as large buildings as compared to the model with ANN in the previous model. It is concluded that the use of CNN is far beneficial than ANN in terms of system response time and complexity to estimate the embodied energy and CO2 emission rate. E4-Model is applied and framed using the basics of deep learning and curve-fitting toolboxes within MATLAB Software. In times to come, a hybrid technique of ANN can be used to add a few more features and applications.

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