Accelerating Whole Life Carbon Assessment in Construction with Artificial Intelligence

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Abstract: *The global effort to reduce carbon emission and mitigate the environmental carbon footprint of the construction industry, along with its impact on climate change, has prompted construction organisations to integrate life cycle carbon assessment into their practices.*

One of the key areas for enhancing sustainability is the immediate evaluation of carbon footprint in the design stage of construction projects. This includes carbon emissions associated with the intrinsic properties of materials, as well as those related to transportation and installation. Additionally, there are carbon emissions linked to the maintenance and operation of the built asset throughout a project life cycle.

This paper aims to accelerate whole-life carbon assessment by integrating artificial intelligence with CarboniCa software, an in-house carbon assessment tool utilised by a major UK construction organisation.

To speed up the evaluation process, a new development is suggested using AI deep-learning neural networks to learn from experience and to estimate carbon footprint, thus reducing time, energy and cost. By leveraging historical construction project data within the CarboniCa software, the experimental results provided a reasonable estimation (R^2 = 0.87) of the whole-life carbon for different building types.

With the integration of deep learning neural networks, the proposed process is expected to improve efficiency by saving time and resources. It will provide designers with rapid guidance during the early design stage, enabling them to reduce the life-cycle carbon impact more effectively.

The paper begins with a literature review on the significance of life cycle carbon assessment in the construction industry, followed by an overview of CarboniCa, a carbon assessment tool. It then explores the integration of artificial intelligence to enhance the software's ability to rapidly evaluate whole-life carbon, thereby promoting sustainability within the built environment.

Keywords: AI; Artificial Intelligence; Construction Industry; Carbon Footprint; Sustainable Construction.

1. INTRODUCTION

The built environment sector produces between 30 and 40% of worldwide carbon emissions (Su et al. 2024). In addition to emitting a large amount of carbon dioxide (CO2) and consuming significant resources, the built environment industry also contributes significantly to social and economic growth (Su et al. 2024). Operational and embodied carbon emissions are the two main types of carbon emissions that are factored into life cycle carbon assessments of buildings. Embodied carbon which sometimes referred to as capital or embedded carbon is carbon emission from the extraction, processing, manufacture, transportation, building, demolition, and disposal of building materials. A cradle-to-cradle assessment of embodied carbon of buildings factors in the material production, off-site transportation, on-site construction, maintenance, and end-of-life phases. The first three phases constitute the cradle-to-site system boundary,

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with studies showing they are the primary contributors to building embodied carbon. Material production processes are the most influential factor, contributing 80 to 95% to the cradle-to-site embodied carbon. Hence, the reduction of embodied carbon in buildings is essential for NetZero future (Zhang et al. 2023). Operational carbon refers to greenhouse gas emissions associated with the energy used for operating the building or the infrastructure during its use over the life cycle (RICS 2024). This includes heating, hot water, cooling, ventilation, lighting systems, equipment, and lifts. Although there is a growing focus on minimising emissions in buildings by optimising building structures to reduce material usage or specifying materials with lower embodied emissions, Ibn-Mohammed et al. (2013) and Kamazani and Dixit (2023) indicated that building performance evaluation should be based on both, embodied and operational emissions. Buildings' operational and embodied carbon is included in whole-life carbon (WLC) computations (Mohebbi et al. 2023). The evaluation of whole life carbon of buildings has become an essential practice in the construction industry for making sure that design options with the lowest carbon footprint are contemplated. However, this practice can be time-consuming in most cases and would require significant input data on carbon factors and quantities of materials in the design, construction, operation and at end-of-life stages, in addition to the energy and water use during operation and their associated carbon.

Artificial intelligence (AI) techniques can accelerate the assessment of a building's whole-life carbon, hence minimising resource requirements and improving accuracy. For example, Su et al. (2024) have used AI techniques to develop a predictive software for measuring carbon emissions during the design phase of buildings so that design solutions can be optimised. Zhang et al. (2024) have also applied AI in predicting the embodied carbon of buildings using different parameters. However, despite these studies, questions still exist on how construction firms can adopt and implement AI solutions to rapidly assess the whole-life carbon emissions of buildings from the design stage. In many cases, construction firms that have embraced the practice of providing whole-life carbon advice to their clients during the design phase conduct these assessments with spreadsheets, bespoke or commercially available software without the use of AI-enabled tools and techniques to accelerate the evaluation process. Therefore, the aim of this study is to present and evaluate a novel approach of integrating AI into the conventional assessment approach adopted by a major construction firm in the UK using deep learning neural networks.

2. LIFE CYCLE ASSESSMENT AND WHOLE-LIFE CARBON

The life cycle assessment (LCA) approach is commonly used to evaluate the overall impact of a building, including its carbon impact. The goal of a building's whole life carbon assessment is to minimise greenhouse gas emissions throughout the building's life cycle via meticulous planning in advance. The European Committee for Standardisation is one organisation whose standards work to guide the EC assessment procedures. However, EC assessment methods vary greatly because of different goals and study scopes. This causes notable differences in study outcomes. Variables that can affect EC have been discovered by previous studies, including building attributes, emission factors, LCA system boundaries, and functional units. However, a systematic understanding of these variables is still lacking (Pan, Teng 2021).

Various factors such as resource extraction, acidification and global warming potential can be used in impact assessment approaches within life cycle assessment (LCA) for buildings. Among these, global warming potential (GWP) is particularly valuable for understanding embodied carbon in the built environment (Kayaçetin and Tanyer 2020). Labaran et al. (2021) examined significant research work on greenhouse gas (GHG) emissions from the building sector, with a focus on how Life Cycle Assessment (LCA) was used to assess these emissions. It methodically looks at research contributions from all over the world, emphasising certain aspects of the construction business, specific countries, locations, and building materials such as steel and cement. Kayaçetin et al. (2020) introduced a novel approach by utilising the Life Cycle Assessment (LCA) framework to assess embodied carbon in the built environment at the neighbourhood level. The results have shown that the average neighbourhood-scale embodied carbon is circa 409.2 kgCO2-eq/m^2, of which 66.6% is contributed by residential structures, 9.1% by structural landscapes, and 24.3% by transportation infrastructure. Arenas et al. (2024) used life cycle assessment (LCA) to evaluate how using sustainable building materials, such as compressed earth blocks and rammed earth, will affect the environment. The findings highlight how sustainable methods have the potential to cut greenhouse gas emissions and boost local economies, as evidenced by the much smaller carbon footprints of sustainable models as compared to those made using traditional materials (Arenas, Shafique 2024). However, these studies do not comprehensively articulate factors such as operational carbon and the recyclability and post-demolition waste of materials which will provide more accurate results while assessing Whole life carbon.

2.1. Whole-life carbon assessment

The fact that emissions happen at various phases of the life cycle presents substantial obstacles to whole-life carbon reduction. To reduce WLC emissions and optimise building design, it is imperative to investigate the operational and embodied emissions of all feasible alternative design options. These possibilities would encompass the building's inputs, processes, and outputs at every step of development (Ministry of Environment. 2019). For example, Gauch et al. (2023) indicated that achieving designs with near-zero heating and cooling energy demands in many climatic conditions is challenging but possible; this can be achieved through measures such as mechanical ventilation with heat recovery, compact building forms, limiting the window-to-wall ratio, having low solar heat coefficients, and designs that meet or come close to Passivhaus standards. Figure 1 shows the whole life of carbon in the life cycle of a building starting from the Product Stage (A1 to A3), followed by the Construction Stage (A4 and A5), In Use Stage ((B1 to B5 = EC) (B6 and B7 = OC)) and End-of-Life Stage (C1 to C4).

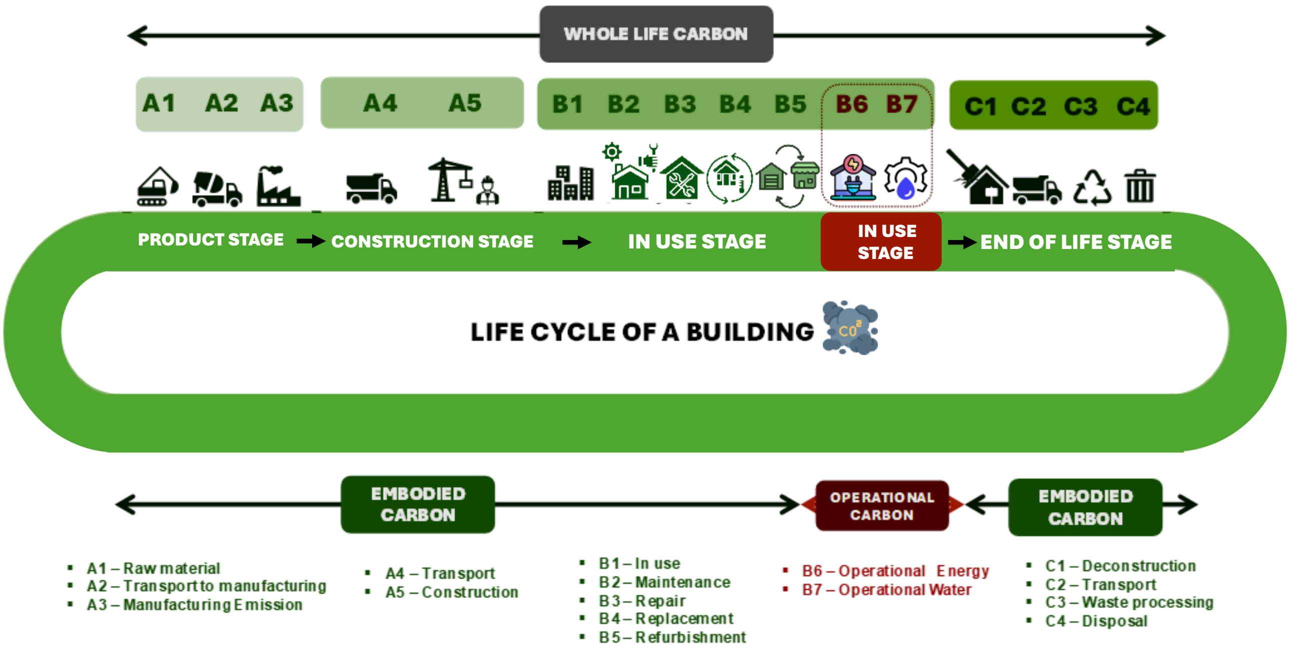

Figure 1: Whole life carbon in the life cycle of a building (Based on RICS 2024)

2.2. Calculation of embodied carbon of buildings

The total cradle-to-gate embodied carbon of a building can be calculated by multiplying the amount of each material utilised in the construction by its respective cradle-to-gate embodied carbon factor, as emphasised in the paper conducted by Akbarnezhad and Xiao (2017a). However, due to uncertainties in the production locations and processes of construction materials and products, the Inventory of Carbon and Energy (ICE) is often used as the primary source for carbon coefficients (Drewniok et al. 2023). However, Gao et al. (2023) has indicated that there is a higher level of inaccuracy when utilising carbon factors from generic databases because the data is derived from various global sources and may not accurately represent the specifications of a particular project. Moreover, to avoid significant discrepancies between estimated and actual values of carbon, (Pomponi and Moncaster, 2018) investigated more transparent understanding of embodied carbon calculations behind buildings. The results have shown that data scarcity is only a problem in some life cycle stages. However, even where data exists, there can be significant variability, which may be related to geographical locations or technological levels. As a result, uncertainties in LCA might raise incorrect information for decision-making (Gavankar et al. 2015; Zhang et al. 2019). Due to these uncertainty factors, calculating the cradle-to-gate carbon for each material is challenging. In practice, a process-based inventory method, input-output (IO) analysis and hybrid approach are commonly used to help manage and understand the carbon emissions of buildings (Cang et al. 2020).

Process-based inventory method

The process-based approach involves a detailed analysis and calculation of carbon emissions at various stages of the life cycle of a product or activity based on LCA. This approach requires carbon emission factors for each single type of material in the building and the corresponding quantities of these materials. This bottom-up analysis provides detailed insights by progressively calculating carbon emissions and assessing the contributions of each material and energy source (Gao et al. 2023) but its applicability may be limited by truncation errors and data scarcity. Therefore, this method is generally suitable when carbon inventory data is available for specific products and materials that are used in the building (Cang et al. 2020).

Input-Output (IO) method

The input-output approach integrates regional input-output tables with the environmental impacts of economic sectors, enabling the comprehensive assessment of carbon emissions across the entire supply chain (Huang et al. 2009). Therefore, the method is more suitable for rapidly estimating carbon emissions in the building industry, but needs to link the monetary values with physical carbon emissions units (Chang et al. 2016); while as Akbarnezhad and Xiao (2017b) has indicated that there are some difficulties in the application of the method to an open economy with substantial noncomparable imports. As a result, existing process-based and input-output (IO) methods exhibited significant limitations in terms of completeness, reliability, and specificity when it comes to embodied carbon emissions (Zhang et al. 2020; Dixit, 2019).

Hybrid Approach

Alternatively, a hybrid approach technique has been proposed, which combines the strengths of both process-based and input-output methods. This approach involves utilising process data, where available and supplementing it with input-output data to comprehensively assess the entire supply chain of a product (Chau et al., 2015). While various types of hybrid methods have been proposed, they often require additional inputs and assumptions, which can result in unexpected uncertainties (Islam et al., 2015). Also, the calculation using the hybrid method can be complicated and time-consuming (Cang et al., 2020). The use of digital technologies that can simplify the time taken to undertake life cycle assessments of buildings therefore continues to attract significant interest.

2.3. Building information modelling and LCA

The use of Building Information Modelling (BIM) in LCA has attracted research interest. A building information model (BIM), which is a digital data store that describes the geometry, material inventories, spatial linkages, and other pertinent details of buildings has also been applied to LCA. Several studies have stressed the potential of BIM to create a life cycle inventory (LCI) for LCA, and the significance of integrating BIM into LCA has grown (Xu et al., 2022). To analyse the embodied carbon in prefabricated buildings, Xu et al. (2022) presented a BIM-integrated LCA solution that achieved a 1% discrepancy with standard manual LCA methods and reduced modelling time, resulting in a 91.5% efficiency gain. To lower building carbon emissions, Arenas et al. (2024) investigated the integration of LCA and BIM, concentrating on sustainable materials such as rammed earth, which was found to have substantially fewer carbon footprints than standard materials. Research on the integration of BIM and LCA identifies adoption barriers and assesses different integration methodologies, but due to project-specific requirements, agreement on the best methodology is still elusive and BIM models will not be available at the early phase of the design or may not exist for a building. Furthermore, as the dynamics between operational and embodied energy in buildings change, so does the significance of thorough Life Cycle Assessments (LCA) that consider the full life cycle of the building. This emphasises the potential for AI-driven solutions to provide increased flexibility and efficiency in handling these complexities. To achieve this, a better understanding of the building parameters that have the most impact on carbon emissions is required.

3. FACTORS INFLUENCING CARBON EMISSIONS FROM BUILDINGS

Gauch et al. (2023) employed global sensitivity analysis to understand the relative importance of architectural design variables at the early design stages on embodied and operational carbon. They found that building compactness, frame material, lowering window-to-wall ratio (WWR), glazed windows, and mechanically ventilated systems with heat recovery were the most important measures for reducing embodied emissions and operational energy. However, Kamazani, Dixit (2023) has indicated that increasing the window-to-wall ratio (WWR) has an advantage in reducing energy consumption and carbon emissions as the embodied energy and embodied carbon of window materials are lower than those of wall components. Sensitivity analysis was also performed by Lotteau et al. (2017) which has indicated that parameters related to building shape and size have a greater impact on embodied energy and embodied carbon per square meter of building area compared to parameters associated with elements such as wall thickness, while glazing ratio is a non-influential factor in terms of embodied carbon in residential building in France.

Moreover, Zhang et al. (2024) conducted a feature importance analysis on their optimal predictive model for embodied carbon, uncovering that the primary influencing factors during the preliminary design phase were material cost, steel use and concrete consumption. In addition, Elastic Net can perform variable selection, encouraging the model to choose a set of correlated features and reducing overfitting. Xikai et al. (2019) used this method, and out of 17 design factors, 12 variables were selected, including number of floors, building height, floor area, building volume, shape coefficient, body coefficient, building height, north-facing window-to-wall ratio, west and east-facing window-to-wall ratio, heat transfer coefficient of roof, heat transfer coefficient of external wall and heat transfer coefficient of glass. Moreover, Zhu et al. (2022) also explored the factors influencing embodied carbon emissions in China and discovered that the building construction area, value of unit building area, indirect emissions intensity, carbon emissions per unit energy consumed, energy intensity, and total factor productivity in the building construction sector have significantly positive impacts. Victoria and Perera, (2018) used multiple estimating methodologies and historical data from four sources to identify that the wall-to-floor ratio and the number of basements were the identified factors when it comes to embodied carbon emission.

Table 1 below shows the influencing factors.

Table 1: Summary of influencing factors from previous work

Author	Influencing Factors
Gauch et al. (2023)	Building compactness, Frame type, Window glazing
Lotteau et al. (2017)	Building shape, Building size
Zhang et al. (2024)	Material cost, Steel consumption, Concrete consumption
Xikai et al. (2019)	Number of storeys, Building Height, Floor area, Building volume, Shape coefficient, Body coefficient, Window-to-Wall Ratio, Heat transfer coefficient of roof, External wall and Glass
Zhu et al. (2022)	Building construction area, Indirect emissions intensity, Carbon emissions per unit energy consumed, Energy intensity, and Total factor productivity
Victoria & Perera (2018)	Wall-to-floor ratio and the Number of basements

4. AI ACCELERATED CARBON ASSESSMENT

The use of Artificial Intelligence (AI) techniques in buildings can help to reduce energy consumption by improving control, automation, and reliability. They can generate predictive data by analysing past data without considering the underlying process. The utilisation of deep learning techniques has led to the incorporation of a greater number of hidden layers in neural networks as Chen et al. (2021) have indicated that this enhancement in architecture has resulted in improved computational efficiency, stability, and overall performance compared to traditional methods. Moreover, due to its considerable potential at every stage of the building lifecycle, artificial intelligence is gaining prominence in the construction sector. This development is consistent with more general patterns of technology progress and real-world application in the context of the construction sector (Yussuf, Asfour 2024). Besides, there are some researchers already performed carbon emission by using machine learning algorithms. For example, Cang et al. (2020) developed a linear fitting regression with a process-based inventory analysis for embodied carbon emissions during the scheme design stage to facilitate the reduction of emissions and enable low-carbon design using various building materials and structural forms. In addition to that the carbon emission figures of 207 residential buildings in Tianjin, China were calculated using the process analysis method, followed by correlation analysis and elastic net techniques to identify 12 key design factors for a predictive regression model incorporating PCR, RF, MLP, and SVR techniques. SVR has demonstrated the highest predictive accuracy among the four models, effectively estimating carbon emission for early stage of the decision-making process (Xikai et al., 2019).

In other cases, Fang et al. (2021) developed the RF-based model showcased a more precise prediction of construction-stage carbon emissions, boasting a lower mean square error (0.7649) and an R2 value of 0.6403. This model utilised data from 38 buildings and considered six influential design parameters: foundation area, above-ground area, underground area, building height, number of above-ground floors, and basement depth. The optimal RF model further revealed the significant impact of the foundation area, underground area, and building height on construction-stage carbon emissions.

It is intriguing that the choice of input features impacts the suitability of machine learning methods and the resulting outcomes. For instance, in the research done by Zhang et al. (2024), models relying solely on a single building height feature yielded inadequate estimates with R^2 values below 0.4 for embodied carbon prediction. However, a combination of features including building height, structural form, seismic fortification intensity, delivery type, geographical region, and material cost proved more effective when employing extremely randomized trees with R^2 and MAPE values of 0.821 and 0.054, respectively. However, if considering more features, prefabrication technique, consumption of steel, concrete, and brick and block, the optimal algorithm is the XGB algorithm instead, achieving R^2 and MAPE values of 0.917 and 0.038, respectively, on the testing dataset.

Su et al. (2023) developed a machine learning model to predict operational carbon emissions. The model evaluated five primary energy sources: space cooling, space heating, hot water, cooking, and home appliances. It considered the temporal fluctuations in occupant profiles, behaviours, and the carbon intensity of energy. In another study conducted by Chen et al. (2021) used artificial intelligence, more precisely a long short-term memory (LSTM) model, to forecast energy consumption and operational CO_2 emissions. Both studies focus exclusively on operational CO_2 emissions, addressing the carbon footprint resulting from the day-to-day functioning of buildings, rather than the embodied carbon associated with construction materials and processes. Nevertheless, Lu et al. (2024) has indicated that to successfully fulfil the objective of “low-carbon buildings” through energy conservation and emission reduction, it is crucial to managing building carbon emissions throughout the design phase because the design process is responsible for eighty percent of the decisions about building carbon emissions. Consequently, once a building enters the construction stage, it becomes challenging to meet additional energy conservation and emission reduction targets. As a result, to address issues in early-stage design, Victoria and Perera, (2018) used regression analysis to establish a parametric embodied carbon prediction model for office buildings in the UK and found that the wall-to-floor ratio and the number of basements were identified as predictors. Su et al. (2024) has employed advanced machine learning methods, such as Artificial Neural Networks (ANN), Support Vector Regression (SVR), and XGBoost to create a predictive tool that can be used throughout the design phase. Their tool is specifically developed to streamline the process of measuring carbon emissions, assist in optimising design choices, and assist in making informed decisions within the building industry. Although the prediction tool performs well, the dataset used in the study is restricted to only 70 project samples from the Yangtze River Delta region, which could potentially impact the accuracy and generalisability of the model. To predict embodied carbon emissions in building structures during the design process, the study conducted by Pomponi et al. (2021) offered a real-time decision-support tool that makes use of machine learning algorithms, such as Artificial Neural Networks (ANN). The tool's ability to produce precise estimates is demonstrated by validating it against commercial finite element analysis (FEA) software.

Table 2: Summary of AI methods from literature

Author	**AI Methods used**	**Variables**	**Materials**	Embodied	Operational	Multi-Objective Optimization
				EC	**OC**	**MOO**
Su et al. (2024)	ANN, SVR XGBOOST	Number of floors, basements, Building area, type of foundation, thickness of floor, wall, type of formwork, prefabrication rate	Concrete, Gravel, Brick, Water, Steel, Wood, Electricity	x	x	
Su et al. (2023)	DT, RF, Polynomial Regression	Space cooling, heating	N/A		x	
Pomponi et al. (2021)	ANN, RF, SVM	Building structure.	Reinforced Concrete, Steel frames, and Engineered timber.	x		
Victoria et al (2018)	Regression	Wall to floor ratio, basement.	N/A	x		
Chen et al (2021)	LSTM	Occupant density, size of the office.	N/A		x	
Xikai, M. et al. (2019)	PCR, RF, MLP, SVR	Number of storeys, Building Height, Floor area, Building volume, Shape coefficient, Body coefficient, Window-to-Wall Ratio, Heat transfer coefficient of roof, External wall and Glass.	Concrete, steel. Mortar, Block, Insulation, Glass, Electricity.		x	
Cang et al. (2020)	Linear fitting analysis	Number of storeys, building structures.	Steel, wall materials, mortar, and concrete.	x		
Fang et al. (2021)	RRF, NSGA-II, NSGA-III, C-TAEA	Foundation area, above-ground area, underground area, building height, number of above-ground floors, and basement depth.	N/A	x		x
Zhang et al (2024)	XGB, Random Forest	Building height, structural form, seismic fortification intensity, delivery type, geographical region, material cost, prefabrication technique, consumption of steel, concrete, and brick and block,	Prefabrication, steel, concrete, brick and block.	x		
Kamazani and Dixit (2023)	Non-dominated sorting genetic algorithm with AI Fuzzy logic	Building orientation, window-to-wall ratio, window construction, and wall construction.	N/A			x
Ascione et al. (2019)	Genetic Algorithm	Building geometry, envelope, systems, and cost considerations.	N/A			x

In summary, there is a growing trend in the field of AI-driven building management to consider a building's whole-life carbon footprint, even if most of the research in this area concentrates on operational or embodied carbon emissions. To address the entire environmental impact of building development and operation, a comprehensive approach is necessary.

4.1. Multi-objective optimisation

In traditional optimisation problems, there is usually only one objective function that needs to be maximised or minimised. However, in the real world, there are often multiple goals to consider, which may conflict with each other. Multi-objective optimisation (MOO) is a process that can simultaneously optimise multiple conflicting objectives. The goal of MOO is to find a set of solutions that represent a compromise between these conflicting goals, called Pareto optimal solutions. The reason these solutions are considered optimal is that it is impossible to improve one goal without worsening at least another goal. Another advantage of the MOO algorithm is that it provides decision-makers with a series of optimal solutions in the decision-making process.

For example, Kamazani and Dixit (2023) used the MOO method to reduce carbon emissions. It involved a three-step iteration process: inputting design variables through the NSGA-II (Non-dominated sorting genetic algorithm), conducting simulations with Energy Plus, and analysing data to compute overall material quantity. Following iteration across these components, a fuzzy decision-making method was employed to select the best solution from the Pareto front solutions. The variables considered primarily encompass building orientation, window-to-wall ratio, window construction, and wall construction. On the other hand, the Fang et al. (2021) used NSGA-II, NSGA-III and C-TAEA MOO algorithms for optimising the building performance optimisation and the convergence degree of C-TAEA was better than NSGA-II and NSGA-III in the study. In addition to that, the research conducted by Ascione et al. (2019) introduced to optimise design variables covering building geometry, envelope, systems, and cost considerations, aiming for optimal solutions. This involved utilising a genetic algorithm (GA) to achieve Pareto optimisation of the building envelope, geometry, and HVAC operation. Subsequently, a smart exhaustive sampling of design scenarios was conducted, with a particular focus on identifying optimal energy systems. Ultimately, the study provided recommended design solutions tailored to the specific needs of designers.

Through the aforementioned related work, it is evident that there is a lack of generic, systematic and comprehensive framework to use AI to evaluate WLC of projects. Consequently, our objective is to develop a deep learning AI model as comprehensive framework that leverages historical data from completed projects. By integrating deep learning AI technology and its applications, this work aims to create a robust decision-support tool that fosters sustainability in the construction process from the initial design stage. By rapidly providing valuable insights, this approach not only streamlines user input time and enhances the user experience but also advances the construction industry and facilitates the development of low-carbon buildings.

5. INTEGRATING AI INTO AN EXISTING WHOLE LIFE CARBON ASSESSMENT SOFTWARE

Morgan Sindall, a top-3 UK construction organisation, has developed CarboniCa software as a carbon reduction tool for use across their projects. The web-based CarboniCa software, which is compliant with the RICS professional standard for whole-life carbon assessment for the built environment and EN15978 has now been used for assessments of over 50 building projects, annually contributing to over 14,500 tonnes of carbon savings. This tool calculates embodied carbon using the preprocess-based inventory method whereby material quantities from a bill of quantities (BOQ) or cost plan are manually entered into the software. These quantities are entered for the various elements in the design, and the elemental breakdown in the CarboniCa software follows the 4th Edition of the BCIS Elemental Standard Form of Cost Analysis. The software has a verified and validated carbon factor database covering all the various materials in buildings they construct. Carbonica also has a carbon factor database that is manually verified and updated periodically, which is used to calculate the embodied carbon. To calculate operational carbon, benchmarked outputs based on building type for both regulated and unregulated loads are used in the calculation where the energy model has not been performed for the design. Where there is an energy model exists for the building, the energy outputs are manually entered into the CarboniCa software to calculate the operational carbon. The output report from CarboniCa comprises a breakdown of the embodied carbon at practical completion (PC-CO2e), embodied carbon over the life cycle of the building (LC-CO2e) and the whole life carbon (WL-CO2e), with accompanying graphs showing the breakdown per building element. These outputs are compared to the client's lifecycle embodied carbon target. The carbon and energy budgets are also compared against industry baselines e.g., London Energy Transformation Initiative (LETI) and Royal Institute of British Architects (RIBA) targets, which are industry-recognised benchmarks. As a carbon reduction tool, the CarboniCa software also has a database of design recommendations that generate specific recommendations for improving carbon savings based on the initial analysis.

To reduce the time that it takes to enter building quantities data into the CarboniCa software, a novel conceptual approach has been proposed to develop a predictive benchmark model for CarboniCa using AI-fuzzy logic and deep learning. The AI model will be trained using previous project data and the experience gathered from experts so that it can predict and input material quantities for a new building under design into the CarboniCa software using building general features and parameters. Building features and parameters for a new design can then be rapidly entered into the predictive benchmark model to generate and input estimated material quantities that will be fed directly into CarboniCa to produce an embodied carbon output for the building as illustrated in Figure 2.

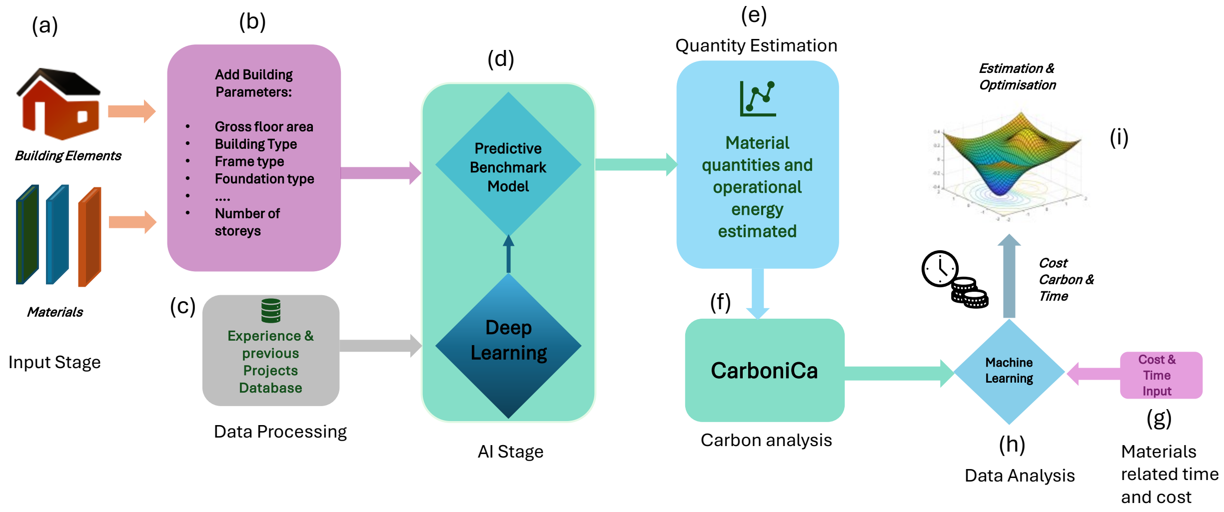

Figure 2: Conceptual diagram of integrating AI into Carbonica

Fuzzy-logic techniques will also be used to develop a multi-objective optimisation model using embodied carbon, cost, order time and installation time as criteria to enhance the design recommendations that are provided to CarboniCa software users (Figure 2-g,h,i). The proposed conceptual model is currently being operationalised for testing and validation using available industry benchmark data as part of a research project. This AI integration into the CarboniCa software will potentially generate productivity savings by reducing the time taken to enter and check user inputs when performing carbon assessments of buildings under design. The AI capability will also enhance the carbon reduction potential of the software as part of the multi-objective optimisation model that is being developed.

6. METHODOLOGY

As previously mentioned, the data was collected from previous construction projects. Data pre-processing involved several steps, including data cleaning, outlier removal, formatting of categorical and numerical variables, handling missing values, feature encoding, and data augmentation (Figure 2-a,b and c). Given that there are just over 50 large new-build projects, a systematic data augmentation technique was employed to enhance the robustness and size of the training datasets. In addition to the original training samples, new data points were generated by introducing small incremental random variations to the actual values, thereby expanding the dataset to help generalisation and reduce AI overfitting. In terms of feature encoding, it was essential to transform categorical variables into a format suitable for deep learning. For feature selection, the Elastic Net method was utilised, as it is well-suited for continuous target variables and can effectively handle feature sets comprising both numerical and categorical variables.

The results of feature selection using Elastic Net, see Figure 3, reveal the relative importance of different building attributes. The size and value of the building emerge as the most critical predictive factors. Notably, gross internal area (GIA) and net internal area (NIA) exhibit the strongest positive influence, suggesting that building size is a primary determinant in predicting the target variable. Following closely, asset value and the number of floors also demonstrate significant positive impacts. These findings align with previous research that has identified these factors as key indicators in carbon prediction (Lotteau et al., 2017; Xikai et al., 2019; Su et al., 2024; Cang et al., 2020; Fang et al., 2021).

Finally, an expert knowledge approach was incorporated into the feature selection process, allowing domain expertise to guide the identification of relevant features based on both theoretical understanding and practical experience. This comprehensive strategy ensured a well-rounded selection of features that enhance model performance. Consequently, the features selected for this regression task are gross internal area (GIA), net internal area (NIA), number of storeys, building cost (asset value), building type, and cooling, heating, and ventilation systems.

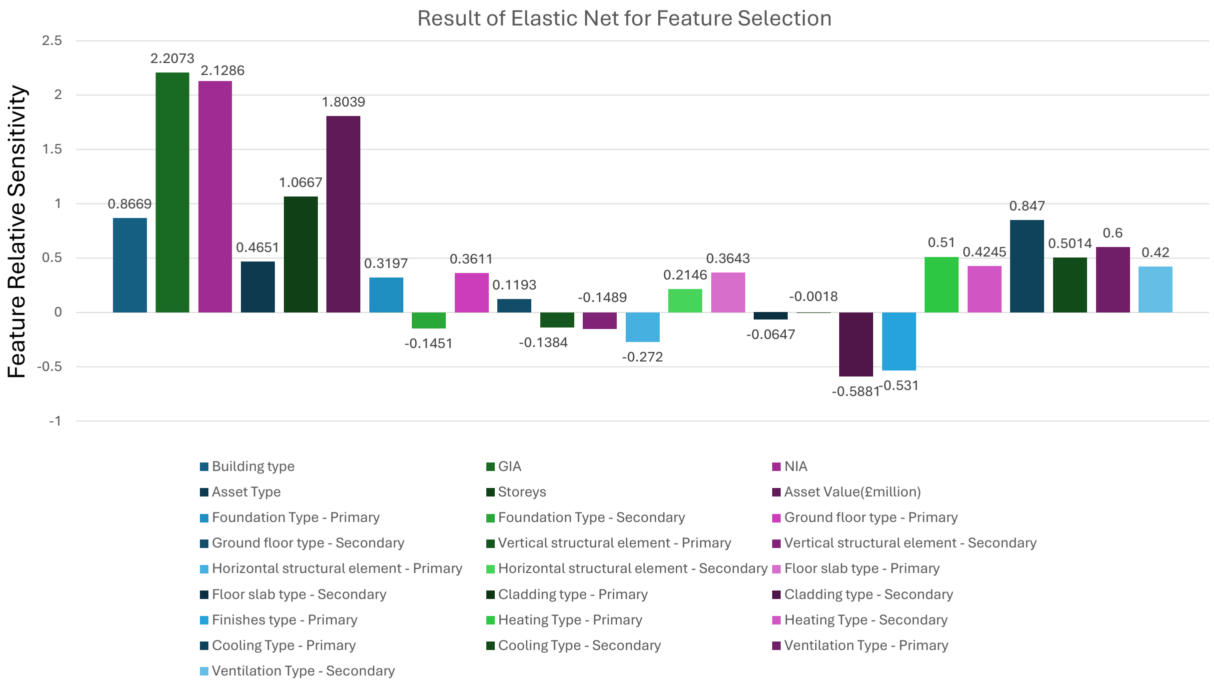

Figure 3: Building's feature selection for the AI model.

6.1 Architecture of the neural network

MATLAB software is utilised in this paper to develop and train the AI model. Model training is a crucial step in constructing any predictive model, particularly when employing neural networks, given their capacity to capture complex patterns and relationships within the data. Neural networks were selected for this task due to their flexibility and effectiveness in modelling non-linear relationships, particularly in cases where input-output mappings are intricate and multi-dimensional.

MATLAB provides various types of neural networks, among which Fitnet, Feedforwardnet, and Cascadeforwardnet are particularly well-suited for regression tasks. In terms of training algorithms, MATLAB offers trainlm, trainscg, trainbr, traingdx, and trainrp, among others. The transfer functions will alternate between logsig, tansig, and purelin, while the output layer will alternate between tansig and purelin. Furthermore, a three-layer hidden structure will be implemented, with each layer initially containing 3 to 9 neurons to evaluate the most suitable neural network configuration for the task. Figure 4 illustrates the architecture of the neural network.

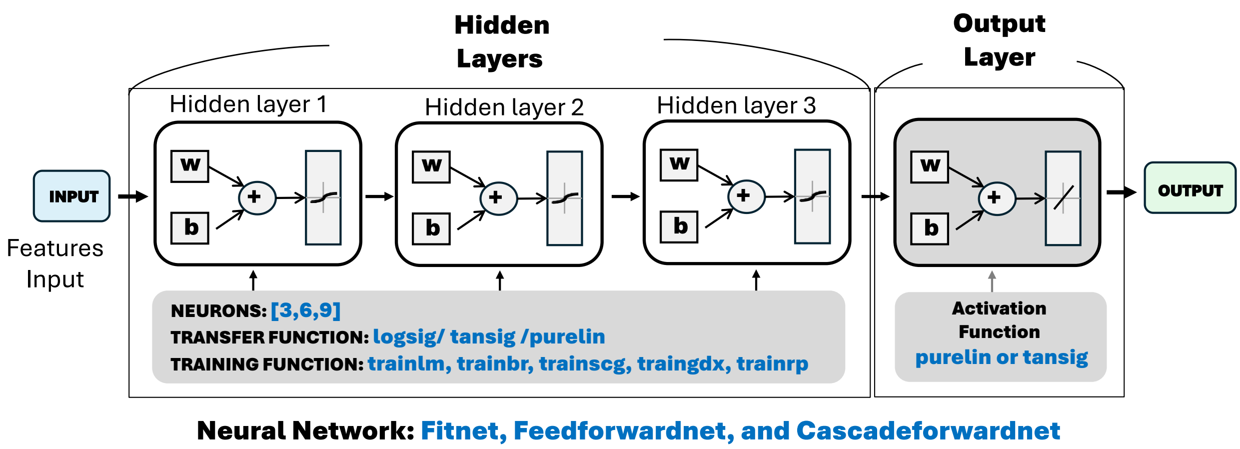

Figure 4: The architecture of the tested neural networks.

7. IMPLEMENTATION AND RESULTS

To determine the optimal configuration for achieving the best results, a for-loop was implemented to iterate through all transfer functions, training algorithms, and neural networks with 3 to 9 neurons. The results are presented in Table 3. This table summarises the performance of various training algorithms and neural networks using different transfer functions, evaluated based on MAPE and R^2 values. The five training algorithms considered are trainlm, trainscg, trainbr, traingdx, and trainrp. Each algorithm was tested across three types of neural networks: Fitnet, Cascadenet, and Feedforwardnet. In all cases, 70% of the data was randomly used for training and 30% was used for testing the neural networks.

Table 3: The performance of different Neural Networks

Algorithm	Neural Network	MAPE (%)	R^2
trainlm	Fitnet	0.27	0.86
	cascadeforwardnet	0.36	0.83
	Feedforwardnet	0.27	0.87
trainscg	Fitnet	0.47	0.76
	cascadeforwardnet	0.83	0.72
	Feedforwardnet	0.52	0.79
trainbr	Fitnet	0.31	0.86
	cascadeforwardnet	0.39	0.81
	Feedforwardnet	0.32	0.82
traingdx	Fitnet	0.85	0.74
	cascadeforwardnet	111.2	0.69
	Feedforwardnet	102.99	0.76
trainrp	Fitnet	0.58	0.79
	cascadeforwardnet	0.74	0.71
	Feedforwardnet	0.6	0.81

Under the trainlm algorithm, the neural networks demonstrate relatively low MAPE differences (ranging from 0.27% to 0.37%) alongside high R^2 values (0.83 to 0.87), indicating strong performance. In contrast, trainscg exhibits higher MAPE differences (0.47% to 0.83%) and lower R^2 values (0.72 to 0.79), making it slightly less effective than trainlm. The results for trainbr are also favourable, with a MAPE difference of approximately 0.3% and R^2 values between 0.80 and 0.86. The traingdx algorithm, however, performed poorly, particularly with Cascadenet and Feedforwardnet networks, showing MAPE differences of 111.2% and 102.99%, respectively, and lower R^2 values (0.69 to 0.76), indicating significant performance issues. Lastly, trainrp falls in the mid-range, with MAPE differences between 0.58% and 0.74% and R^2 values from 0.71 to 0.81, offering acceptable performance but not reaching the standards of trainlm and trainbr.

In summary, while trainlm and trainbr emerged as the best-performing algorithms, achieving lower MAPE and higher R^2 values, trainlm stands out for its speed advantage due to its ability to dynamically adjust parameters, modify weights, and accelerate convergence, thereby enhancing the efficiency of each iteration. Conversely, traingdx performed notably poorly, particularly in the cascadeforwardnet and Feedforwardnet models.

As a result, the optimal neural network architecture is presented in Figure 5. A feedforward neural network model has been identified as the most suitable for this study in predicting the desired outcomes. The model consists of an input layer corresponding to the input features and an output layer that generates predictions. The architecture includes three hidden layers, with neuron configurations optimised through experimentation.

The hidden layers are implemented using the hyperbolic tangent sigmoid activation function, 'tansig', while the output layer employs the linear activation function, 'purelin'. This configuration enables the hidden layers to capture complex non-linear relationships within the data while ensuring that the output layer can effectively model continuous values, which is also essential for regression tasks.

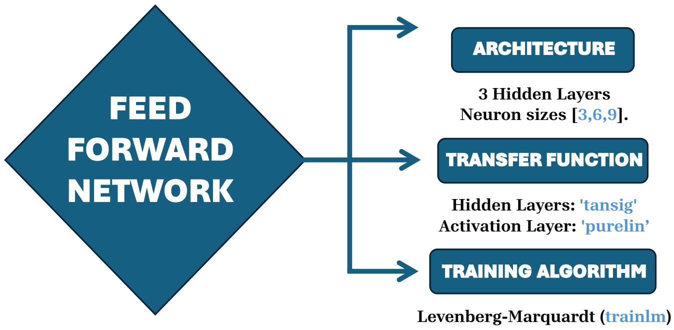

Figure 5: The selected neural network for Whole Life Carbon (WLC) prediction.

8. CONCLUSION

This study has reviewed the literature on LCA and WLCA in the built environment, identifying challenges related to data variability, sufficiency, completeness, reliability, and the time-consuming nature of assessments at the building scale. Despite the use of digital tools such as BIM in LCA, the integration of AI into carbon assessments throughout a building's lifecycle has been discussed, including the building factors that influence these emissions. The insights from this review have informed the development of a novel conceptual approach for integrating AI into an existing in-house carbon reduction software used by a major UK contractor. The proposed AI integration approach is under development at the time of writing this paper, with the next phase being industrial testing and validation of the model's efficacy using circa 100 projects. It is anticipated that the AI engine will offer an option within the CarboniCa software environment to rapidly assess whole life carbon emission, leveraging learning from past projects. While the dataset includes over 50 recent projects, generalisability issues may arise in the future and hence the plan is to expand the number of projects to enhance the generalisation with any future project variations.

Looking ahead, the integration of multi-objective optimisation using fuzzy logic for alternative material recommendation will enhance the carbon reduction potential of the software by providing dynamic, responsive design recommendations that consider carbon, time, and cost. This will enable data-driven decision-making that maximises quality and speed by harnessing past project data. A broader implication of this study is that further research to develop, test, and integrate the proposed AI model into the CarboniCa software will provide practical use cases for AI adoption in the construction sector. This could serve as a solution for improving the sustainability performance of construction projects, contributing to net-zero ambitions. However, there is still room for experimentation, as certain factors such as soil type, region, WWR or local economic conditions are still to be explored in future studies.

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