21st International Conference on Sustainable Energy Technologies

12 to 14th August 2024, Shanghai, China

Sustainable Energy Technologies 2024
Conference Proceedings: Volume 1

WSSET

World Society of Sustainable Energy Technologies

Proceedings of the 21st International Conference on Sustainable Energy Technologies

SET2024

12 – 14th August 2024, Shanghai, China

Edited by
Professor Saffa Riffat

Supported by SET2024 Conference Organising Committee

Chair: Professor Saffa Riffat
Co-Chair: Professor Zhongzhu Qiu
Editors: Dr Ziwei Chen
Dr Tianhong Zheng
Dr Yanan Zhang
Dr Yi Fan
Ms Zeny Amante-Roberts

Reference to a conference paper:
To cite a paper published in these conference proceedings, please substitute the highlighted sections of the reference below with the details of the article you are referring to:
Author(s) Surname, Author(s) Initial(s), 2024. 'Title of paper'. In: Riffat, Su. ed., **Sustainable Energy Technologies**: Proceedings of the 21st International Conference on Sustainable Energy Technologies, 12-14th August 2024, Shanghai, China. University of Nottingham: Buildings, Energy & Environment Research Group. Pp XX-XX. Available from: nottingham-repository.worktribe.com/ [Last access date].

ISBN-13 978-0-85358-356-1
Version: 01.12.2024

#4: Rapid evaluation of embodied carbon of buildings' lifecycle using artificial intelligence

Amin AL-HABAIBEH[1], Emmanuel MANU[2], Tim CLEMENT[3], Bubaker SHAKMAK[1], Janani SELVAM[1], Tsai-Hsuan LIN[1]

[1] Product Innovation Centre, School of Architecture, Design and The Built Environment, Nottingham Trent University, UK
[2] Centre for the Built Environment, School of Architecture, Design and The Built Environment, Nottingham Trent University, UK
[3] Morgan Sindall Construction, UK

Abstract: The global drive to reduce carbon emissions and the footprint of the construction industry and its effect on climate change has led to construction organisations integrating life cycle carbon assessment into their activities. One of the key areas for enhancing sustainability is the reduction of embodied carbon in the materials. This comprises the carbon associated with intrinsic features of the materials themselves, transportation, and installation-related emissions. There is also the carbon emission associated with the maintenance, and operation of the built assets during their life cycles. To enable the rapid evaluation of the whole-life carbon, i.e. carbon emission during design, construction, operational and end-of-lifephase of buildings, this study presents a novel approach to integrating artificial intelligence (AI) into existing practices with focus onembodied carbon. This novel approach comprises the integration of data using AI to provide quick guidance for designers during the early design stage of the process to reduce the life-cycle carbon impact. This approach will exploit a wide range of datasets from up-to-date Carbon databases and previous construction projects and their carbon footprint. This will allow a reasonable estimation of the carbon footprint of different design choices for clients and designers, allowing them to collaborate rapidly reaching an optimum configuration and material selection for their buildings. Current practice involves manual input of carbon data into carbon estimationsoftware to enable the output. With the integration of fuzzy logic and deep-learning neural networks, the new proposed process will contribute to time savings and enhanced decision-making. The paper begins with a literature review of the importance of monitoring carbon emissions in the construction industry, followed bya discussion of CarboniCa Software, an in-house carbon assessment package used by a major UK construction organisation. And finally, an analysis of how AI capability will support the software for rapid evaluation of whole life carbon will be presented. This application highlights the importance of AI towards a more efficient and sustainable future.

Keywords: Artificial Intelligence; Construction; Low Carbon; Sustainability; Rapid Evaluation

1. INTRODUCTION

The construction industry produces between 30 and 40% of carbon emissions worldwide (Su et al. 2024). In addition to emitting a large amount of carbon dioxide (CO2) and consuming significant resources, the construction industry also contributes significantly to social and economic growth (Su et al. 2024). Operational and embodied carbon emissions are the two types of carbon emissions that are factored into life cycle carbon assessments of buildings. Embodied carbon, which is sometimes referred to as capital carbon is carbon emission from the extraction, processing, manufacture, transportation, building, demolition, and disposal ofbuilding 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, with studies showing they are the primary contributors to building embodied carbon. Material production is the most influential factor, contributing 80 to 95% to the cradle-to-site embodied carbon. Therefore, the reduction of embodied carbon in buildings is essential for a carbon-neutral society (Zhang et al. 2023). Operational carbon refers to greenhouse gas emissions associated with the energy used for the operation of buildings or infrastructure during its use over its life cycle (RICS 2024), including heating, hot water, cooling, ventilation, lighting systems, equipment, and lifts. Even though there is a growing focus on reducing emissions in buildings by optimising building structures to minimise 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 embodied and operational emissions. Buildings' operational and embodied carbon is included in whole-life carbon (WLC) calculations (Mohebbi et al. 2023). The assessment of whole life carbon of buildings has become an important practice in the construction industry for ensuring that design options with the lowest carbon footprint are considered. However, this practice can be time-consuming and requires significant data on carbon factors and quantities of all the materials in the design, construction, operation and at end-of-life stages, plus the energy and water use during operation and its associated carbon.

Artificial intelligence (AI) techniques have the capabilities to accelerate the assessment of a building's whole-life carbon, minimise resource requirements and improve accuracy. Su et al. (2024) have used AI techniques to develop a predictive tool 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 various parameters. However, despite these studies, questions still exist on how construction firms have adopted and implemented AI solutions to rapidly assess the whole-life carbon emissions of buildings they design and build for their clients. 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 any AI-enabled tools and techniques to accelerate this process. The aim of this study was to evaluate a novel approach for integrating AI into the conventional assessment approach adopted by a major construction firm in the UK.

The rest of the paper discusses life cycle assessments and whole-life carbon in buildings, factors that influence carbon emissions in buildings and AI-accelerated carbon assessments. This is followed by the discussion of a novel approach for integrating AI into an existing WLC assessment tool used by a major construction firm in the UK before concluding the study.

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 through meticulous planning in advance. The European Committee for Standardisation is one organisation whose standards work to standardise 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 byprevious studies, including building attributes, emission factors, LCA system boundaries, and functional units. However, a systematic understanding of these variables is 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 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/m2, 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 neglect 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).

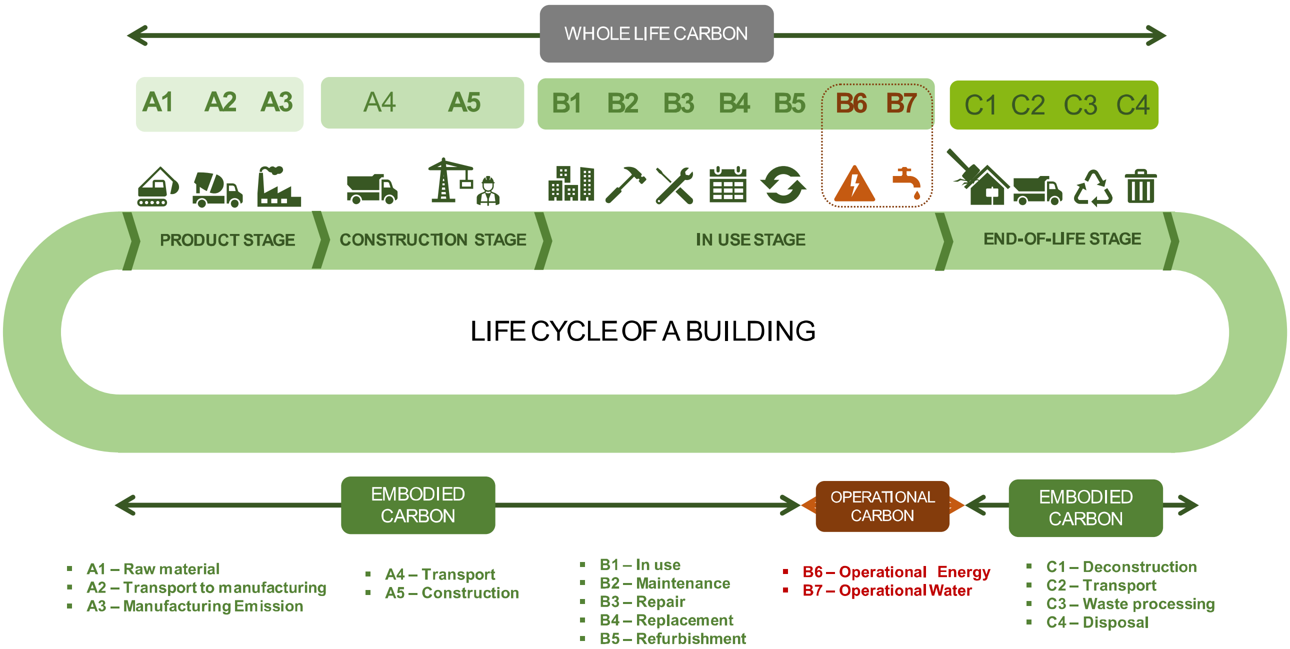

Figure 1: Whole life carbon in the life cycle of a building (Based on RICS 2024)

2.2. Calculation of embodied from 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 the more transparent understanding of embodied carbon calculations behind the 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 location or technological level. 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 estimating carbon emissions in the building industry rapidly 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 application to an open economy with substantial non-comparable 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 geometry, material inventories, spatial linkages, and other pertinent details of buildings hasalso 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 reduce 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 such 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 buildinglifecycle, 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 who have 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 of 207 residential buildings in Tianjin, China was 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 R2 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 R2 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 R2 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 isresponsible 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 generalizability of the model. To predict embodied carbon emissions in building structures during the design process, the studyconducted 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.

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.

Table 2: Summary of AI methods from previous work

Author	AI Methods used	Variables	Materials	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	Occupancy 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

For example, Kamazani and Dixit (2023) utilised 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 optimize design variables covering building geometry, envelope, systems, and cost considerations, aiming for optimal solutions. This involved utilising a genetic algorithm (GA) to achieve Pareto optimization 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.

Our objective is to create an AI model that uses historical data from completed projects to automate input and material optimisation for new construction designs considering these difficulties. This model aims to simultaneously optimise cost, time, and carbon emissions while taking into account a variety of architectural characteristics. Through the integration of cutting-edge machine learning techniques and the application of experiences learned from past projects, our goal is to develop a powerful decision- support tool that improves the sustainability of the construction process starting with design. By offering more precise and useful information, this method aims to progress the construction industry and help create truly low-carbon buildings.

4.2. 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 on over 50 large building projects (over £5m), 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. Building parameters for a new design can then be rapidly entered intothe 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.

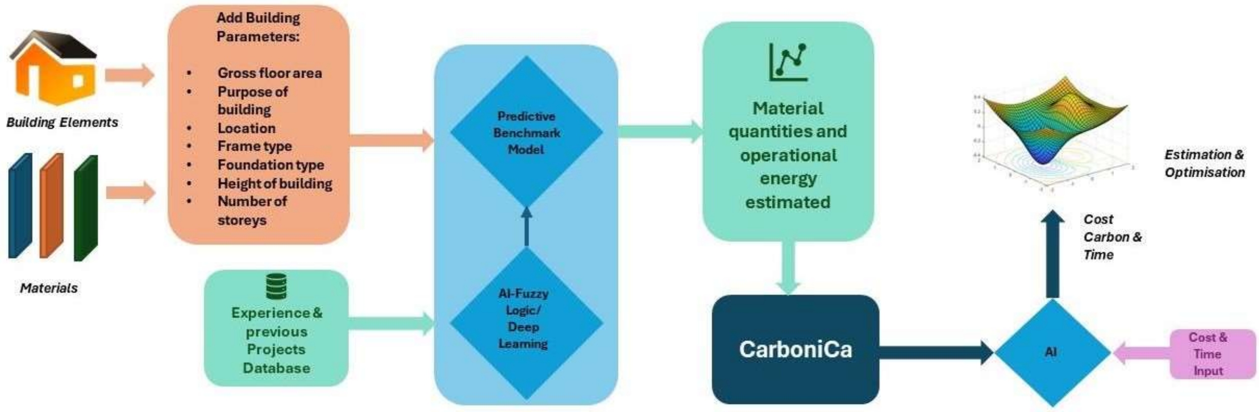

Figure 2: Conceptual diagram of integrating AI into Carbonica

AI and 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. The proposed conceptual model is currently being operationalised for testing and validation using available industry benchmark data as part of an ongoing 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.

5. CONCLUSION

This study has provided a review of the literature on LCA and WCA in the built environment, identifying the challenges of data variability, sufficiency, completeness, reliability and the time-consuming nature of assessments at a building scale. Despite the use of digital tools such as BIM in LCA, the need for integrating AI into the embodied carbon assessments across the lifecycle of buildings have been discussed, including the building factors that influence these emissions. These insights have been used to propose a novel conceptual approach for integrating AI into existing in-house carbon reduction software for a major UK contractor. The conceptual AI integration approach presented in this study is currently under development, with the phases that follow industry testing and validation of the model performance. It is anticipated that the AI engine will provide an option within the CarboniCa software environment for rapidly evaluating embodied carbon, based on learning from past projects and experience from experts. This multi-objective optimisation will also enhance the carbon reduction potential of the software by offering design recommendations that are dynamic and responsive to carbon, time and cost considerations. This will lead to data-driven decision-making where quality and speed can be maximised by exploiting past project data. As a wider implication, the further study being conducted to develop, test and integrate the proposed AI model into the existing CarboniCa software will ultimately provide a practical use case of AI adoption and integration within the construction sector and in a construction organisation, with this specific instance being as a solution for improving the sustainability performance of construction projects as part of net-zero ambitions.

6. ACKNOWLEDGEMENT

The authors would like to thank Innovate UK for funding this project under BridgeAI programme, project ref 1715: AI-Accelerated Carbon Assessment for the Construction Industry (AIACACI).

7. REFERENCES

Akbarnezhad, A. and Xiao, J., 2017. Estimation and minimization of embodied carbon of buildings: a review. Buildings, 7(1), p.5.

Arenas, N.F., Shafique, M., 2024. Reducing embodied carbon emissions of buildings – a key consideration to meet the net zero target. Sustainable Futures, 7. 10.1016/j.sftr.2024.100166.

Ascione, F. et al., 2019. A new comprehensive framework for the multi-objective optimization of building energy design: Harlequin. Applied Energy, 241, pp.331–361. 10.1016/J.APENERGY.2019.03.028.

Cang, Y. et al., 2020. A new method for calculating the embodied carbon emissions from buildings in schematic design: Taking "building element" as basic unit. Building and Environment, 185, p.107306. 10.1016/J.BUILDENV.2020.107306.

Cang, Y. et al., 2020. Prediction of embodied carbon emissions from residential buildings with different structural forms. Sustainable Cities and Society, 54. 10.1016/j.scs.2019.101946.

Chang, Y. et al., 2016. The embodied air pollutant emissions and water footprints of buildings in China: a quantification using disaggregated input–output life cycle inventory model. Journal of Cleaner Production, 113, pp.274–284. 10.1016/J.JCLEPRO.2015.11.014.

Chau, C.K., Leung, T.M., Ng, W.Y., 2015. A review on Life Cycle Assessment, Life Cycle Energy Assessment and Life Cycle Carbon Emissions Assessment on buildings. Applied Energy, 143(1), pp.395–413. 10.1016/J.APENERGY.2015.01.023.

Chen, C.Y., Chai, K.K., Lau, E., 2021. AI-Assisted approach for building energy and carbon footprint modeling. Energy and AI, 5. 10.1016/j.egyai.2021.100091.

Drewniok, M.P. et al., 2023. Mapping material use and embodied carbon in UK construction. Resources, Conservation and Recycling, 197. 10.1016/j.resconrec.2023.107056.

Fang, Y., Lu, X., Li, H., 2021. A random forest-based model for the prediction of construction-stage carbon emissions at the early design stage. Journal of Cleaner Production, 328, p.129657. 10.1016/J.JCLEPRO.2021.129657.

Gao, H. et al., 2023. A review of building carbon emission accounting and prediction models. Buildings, 13(7), p.1617.

Gauch, H.L. et al., 2023. What really matters in multi-storey building design? A simultaneous sensitivity study of embodied carbon, construction cost, and operational energy. Applied Energy, 333. 10.1016/j.apenergy.2022.120585.

Gavankar, S., Anderson, S., Keller, A.A., 2015. Critical Components of Uncertainty Communication in Life Cycle Assessments of Emerging Technologies: Nanotechnology as a Case Study. Journal of Industrial Ecology, 19(3), pp.468–479. 10.1111/jiec.12183.

Huang, Y.A., Weber, C.L., Matthews, H.S., 2009. Categorization of scope 3 emissions for streamlined enterprise carbon footprinting. Environmental Science and Technology, 43(22), pp.8509–8515. 10.1021/es901643a.

Ibn-Mohammed, T. et al., 2013. Operational vs. embodied emissions in buildings—A review of current trends. Energy and Buildings, 66, pp.232–245. 10.1016/J.ENBUILD.2013.07.026.

Islam, H., Jollands, M., Setunge, S., 2015. Life cycle assessment and life cycle cost implication of residential buildings—A review. Renewable and Sustainable Energy Reviews, 42, pp.129–140. 10.1016/J.RSER.2014.10.006.

Kamazani, M.A., Dixit, M.K., 2023. Multi-objective optimization of embodied and operational energy and carbon emission of a building envelope. Journal of Cleaner Production, 428. 10.1016/j.jclepro.2023.139510.

Kayaçetin, N.C., Tanyer, A.M., 2020. Embodied carbon assessment of residential housing at urban scale. Renewable and Sustainable Energy Reviews, 117. 10.1016/j.rser.2019.109470.

Labaran, Y.H., Mathur, V.S. and FAROUQ, M.M., 2021. The carbon footprint of construction industry: A review of direct and indirect emission. Journal of Sustainable Construction Materials and Technologies, 6(3), pp.101-115.

Lotteau, M., Loubet, P., Sonnemann, G., 2017. An analysis to understand how the shape of a concrete residential building influences its embodied energy and embodied carbon. Energy and Buildings, 154, pp.1–11. 10.1016/J.ENBUILD.2017.08.048.

Lu, M. et al., 2024. Methods for Calculating Building-Embodied Carbon Emissions for the Whole Design Process. Fundamental Research. 10.1016/j.fmre.2022.07.015.

Mohebbi, G. et al., 2023. Comparative analysis of the whole life carbon of three construction methods of a UK-based supermarket.

Building Services Engineering Research and Technology, 44(3), pp.355–375. 10.1177/01436244231161070.
Pan, W., and Y. Teng. "A systematic investigation into the methodological variables of embodied carbon assessment of buildings." Renewable and Sustainable Energy Reviews 141 (2021): 110840.

Pomponi, F. et al., 2021. Enhancing the Practicality of Tools to Estimate the Whole Life Embodied Carbon of Building Structures via Machine Learning Models. Frontiers in Built Environment, 7. 10.3389/fbuil.2021.745598.

Pomponi, F., Moncaster, A., 2018. Scrutinising embodied carbon in buildings: The next performance gap made manifest. Renewable and Sustainable Energy Reviews, 81, pp.2431–2442. 10.1016/J.RSER.2017.06.049.

RICS, 2024. Whole life carbon assessment for the built environment RICS PROFESSIONAL STANDARD [eBook]. Available at: www.rics.org.

Su, S. et al., 2024. Considering critical building materials for embodied carbon emissions in buildings: A machine learning-based prediction model and tool. Case Studies in Construction Materials, 20. 10.1016/j.cscm. 2024.e02887.

Su, S. et al., 2023. Temporal dynamic assessment of household energy consumption and carbon emissions in China: From the perspective of occupants. Sustainable Production and Consumption, 37, pp.142–155. 10.1016/j.spc.2023.02.014.

Victoria, M.F., Perera, S., 2018. Parametric embodied carbon prediction model for early stage estimating. Energy and Buildings, 168, pp.106–119. 10.1016/j.enbuild.2018.02.044.

Xikai, M. et al., 2019. Comparison of regression models for estimation of carbon emissions during building's lifecycle using designing factors: a case study of residential buildings in Tianjin, China. Energy and Buildings, 204, p.109519. 10.1016/J.ENBUILD.2019.109519.

Xu, J. et al., 2022. BIM-integrated LCA to automate embodied carbon assessment of prefabricated buildings. Journal of Cleaner Production, 374. 10.1016/j.jclepro.2022.133894.

Yussuf, R.O. and Asfour, O.S., 2024. Applications of artificial intelligence for energy efficiency throughout the building lifecycle: An overview. Energy and Buildings, p.113903.

Zhang, X. et al., 2023. Characteristics of embodied carbon emissions for high-rise building construction: A statistical study on 403 residential buildings in China. Resources, Conservation and Recycling, 198. 10.1016/j.resconrec.2023.107200.

Zhang, X., Liu, K., Zhang, Z., 2020. Life cycle carbon emissions of two residential buildings in China: Comparison and uncertainty analysis of different assessment methods. Journal of Cleaner Production, 266, p.122037. 10.1016/J.JCLEPRO.2020.122037.

Zhang, Xiaocun et al., 2024. Predictive models of embodied carbon emissions in building design phases: Machine learning approaches based on residential buildings in China. Building and Environment, 258. 10.1016/j.buildenv.2024.111595.

Zhu, C. et al., 2022. Factors influencing embodied carbon emissions of China's building sector: An analysis based on extended STIRPAT modeling. Energy and Buildings, 255, p.111607. 10.1016/J.ENBUILD.2021.111607