Rapid Evaluation of Cost and Whole Life Carbon of Buildings Using Artificial Intelligence

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***Abstract*— The global drive to reduce carbon footprint and optimise costs in the construction industry has led to integrating Whole Life-Cycle Carbon (WLC) and cost assessments into industry practices. One of the key points is reducing embodied carbon in materials and accounting for emissions and costs during transportation, installation, and the operation of built assets. This study presents a novel approach of using Artificial Intelligence (AI) to rapidly evaluate both Whole Life-Cyle Carbon (WLC) and costs, enabling an enhanced and rapid decision-making during the early design stages. By leveraging data from Building Cost Information Service (BCIS) database and carbon databases from past projects of a top construction firm in UK, AI is found to provide real-time guidance for optimising material choices and configurations, hence balancing sustainability with budget considerations. The proposed integration of using AI techniques such as neural networks into existing carbon and cost estimation tools, such as CarboniCa Software, aims to streamline the current data entry process and provide a rapid data analysis. This not only saves time but also reduces cost of implementation and enhances productivity. This paper outlines the use of AI techniques to predict embodied carbon and cost of construction projects from key characteristic features of buildings. The results show that AI can be used to predict the expected outputs with high accuracy, consequently providing productivity improvements and reducing time and cost of implementation. The suggested approach highlights the future role of AI in driving more sustainable, productive and cost-effective construction practices.**

Keywords*— *AI; Neural Networks; Carbon; Construction.

I. INTRODUCTION

While the construction industry plays a crucial role in driving social developments, the United Nations Environment Programme [1] reports that the buildings and construction sector is the largest source of greenhouse gas emissions, accounting for 37% of global emissions. This makes it one of the primary contributors to climate change. Consequently, the construction industry faces significant challenges in balancing environmental sustainability, requiring a strong focus on reducing carbon emissions especially operational and embodied carbon, both of which are essential elements in life cycle carbon assessments for buildings.

Embodied carbon, sometimes referred to as capital carbon, encompasses the emissions generated throughout the lifecycle of building materials from extraction, processing, and manufacturing; followed by transportation, construction, demolition and disposal. A comprehensive "cradle-to-cradle" assessment factors in all these stages, with material production contributing the most, accounting for 80 to 95% of cradle-to-site embodied carbon. Operational carbon refers to the emissions associated with the energy used during a building's use, such as heating, cooling and ventilation [2]. Both types of emissions are critical in calculating whole-life carbon (WLC), an essential practice in the construction industry for selecting design options with the lowest carbon footprint.

However, conducting accurate WLC assessments is a complex and time-consuming process. It requires vast amounts of data entry on material and energy usage throughout the entire life cycle of a building. This has become a major bottleneck in the efforts to achieve carbon assessment. In addition, Lu et al.[3] indicates 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 emission reduction targets.

Nevertheless, CarboniCa is an intelligent carbon calculation tool developed by Morgan Sindall, a leading UK construction organisation, to address the challenges of carbon emissions in the construction industry. It is designed to measure whole life carbon emissions in accordance with Royal Institution of Chartered Surveyors (RICS) professional standards throughout the design, construction, and lifecycle of a building. This web-based software, compliant with both the RICS professional standard for whole-life carbon assessment and EN15978, has been utilised for assessments on over 50 large building projects, contributing to annual carbon savings of more than 14,500 tonnes. The tool calculates carbon emissions using a preprocess-based inventory method, allowing users to manually input material quantities from a bill of materials or cost plan. These quantities are specified for different design elements, with the software's elemental breakdown adhering to the 4th Edition of the BCIS Elemental Standard Form of Cost Analysis. CarboniCa also includes a verified and validated carbon factor database that covers all materials used in Morgan Sindall's construction projects, which is regularly updated and manually verified to ensure its accuracy.

On the other hand, AI plays a crucial role, possessing the potential to revolutionise the way carbon assessments are conducted by significantly reducing the time required and improving the efficiency of the assessment process. AI techniques, such as those employed by Su et al. [4], have been utilised to develop predictive tools that optimise carbon efficiency in building designs from the outset; concurrently, Zhang et al. [5] have applied AI to predict embodied carbon based on various building parameters.

Thus, by facilitating faster carbon assessments, AI not only aids construction companies in making quicker decisions but also offers clients more sustainable, low-carbon options

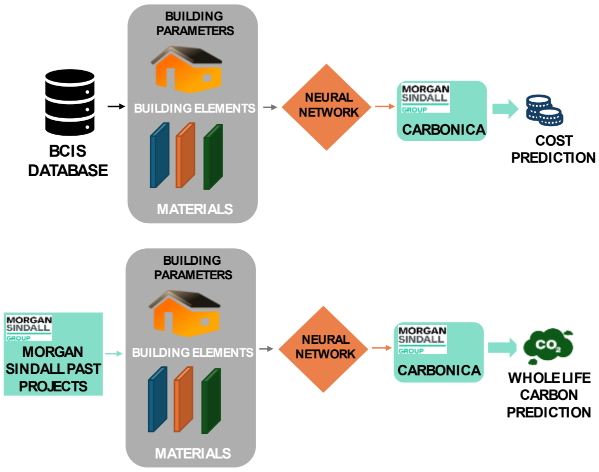

Fig. 1. The use of AI with CarboniCa software to estimate cost and WLC.

A. Aim and Objective

This study aims to evaluate, within the CarboniCa framework, the use of AI and its integration into Cost and WLC assessment processes as shown in the **Error! Reference source not found.**. By applying deep learning, not only streamline the process, but also significantly enhance the efficiency of carbon emission and cost evaluations. The objective is to enable more data-driven, and environmentally friendly decision-making process based on historical data from past projects by developing an AI model that can effectively leverage valuable insights derived from previous projects and BCIS databases to rapidly estimate the carbon emission and cost of the building to improve the sustainability of the entire construction process from the earliest stages.

Furthermore, this paper explores the various factors that influence carbon emissions in buildings, providing a thorough analysis of how these factors interact and contribute to the overall carbon footprint. It also examines the pivotal role that AI can play in accelerating the speed of cost and carbon assessments and offers an in-depth discussion on how AI can be seamlessly integrated into Carbonica tools, thereby laying the foundation for more sustainable and eco-conscious building practices in the future.

II. Literature Review

A. Factors for Achieving Low Carbon Buildings

Recent studies have highlighted several critical factors that contribute to carbon emissions in building design through data analysis, focusing on both embodied and operational carbon. Kamazani and Dixit [6] suggested that increasing the window-to-wall ratio (WWR) could be advantageous, as the embodied energy and carbon associated with window materials are lower than those of wall components; furthermore, Lotteau et al. [7] supported this perspective, revealing that building shape and size have a more substantial impact on embodied energy and carbon per square metre compared to factors such as wall thickness; while the glazing ratio was found to be non-influential for embodied carbon in residential buildings in France. In Contrast, Gauch et al. [8] utilised sensitivity analysis to evaluate the impact of architectural design variables during the early design stages, identifying key measures such as building compactness, frame material, the use of glazed windows, and mechanically ventilated systems and a reduced window-to-wall ratio (WWR). The WWR results were opposite to the above two references as heat gain from windows and their lower embodied would reduce embodied emissions and operational energy. Additionally, Zhang et al. [5] conducted a feature importance analysis, uncovering that material cost, steel use, and concrete consumption are primary influences during the preliminary design phase. Moreover, Xikai et al. [9] identified 12 significant design variables from a total of 17 factors, including building height, floor area, and various heat transfer coefficients. And Zhu et al. [10] examined embodied carbon emissions in China and found that factors such as building construction area and indirect emissions intensity had a significant impact on overall emissions. Furthermore, Victoria and Perera [11] utilised multiple estimation methodologies to determine that the wall-to-floor ratio and the number of basements are crucial in influencing embodied carbon emissions. Last, Giannelos et al. [12] introduced the application of shallow neural networks for implementing time series forecasting of CO2 emissions related to the construction industry. Interestingly, under the same methods, carbon emissions vary across different countries, suggesting that region could also be an important variable.

Collectively, these studies emphasise the importance of understanding and optimising factors such as frame material, window-to-wall ratio (WWR), building shape and size, material cost, steel and concrete use, building height, floor area, heat transfer coefficients, building construction area, and the wall-to-floor ratio to achieve more sustainable building designs.

B. AI Accelerated carbon assessment

There is a growing trend in the field of AI-driven building management to consider a building's whole-life carbon footprint. It is because the use of Artificial Intelligence (AI) techniques can generate predictive data by analysing past data and buildings' key features without considering the underlying process. The utilisation of both machine learning and deep learning techniques has led to the incorporation of a greater number of hidden layers in neural networks as Chen et al. [13] 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, AI 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 [14].

Moreover, some researchers have already predicted carbon emission by using machine learning algorithms. For example, Su et al. [4] employed advanced machine learning techniques, including Artificial Neural Networks (ANN), Support Vector Regression (SVR), and XGBoost, to create a predictive tool for use throughout the design phase. This tool was developed to streamline carbon emission measurements, optimise design choices, and support informed decision-making within the construction industry. While the tool performs well, its dataset was limited to only 70 project samples from the Yangtze River Delta region, which may impact the model's accuracy and generalisability.

Jin [15] utilised both the General Regression Neural Network (GRNN) and multiple linear regression models for predicting carbon emissions. The MLR model yielded an R^2 value of 0.7001, significantly lower than the GRNN model's R^2 value of 0.7673. Additionally, the GRNN model surpassed the MLR model in forecasting CO2 emissions, achieving a Mean Absolute Percentage Error (MAPE) of 2.53%, a Relative Error (RE) of 5.40%, and a Root Mean Square Error (RMSE) of 0.40. In a similar study, Pino-Mejías et al. [16] implemented both MLP regression and Artificial Neural Networks (ANN) models for CO2 emissions. The MLP model demonstrated excellent performance, achieving an R^2 value exceeding 0.9 for both cooling and heating carbon emissions. Moreover, a three-layered deep learning model utilising a logistic activation function achieved an outstanding R^2 value of 1. Nevertheless, Acheampong and Boateng [17] evaluated the applicability of the feedforward multi-layer perceptron (FFMLP) with back-propagation (BP) to optimise the ANN model for predicting CO2 emission intensity in Australia, Brazil, China, India, and the USA. The sigmoid function was chosen as the activation function for the output layer, while the rectifier function (ReLU) was utilised in the hidden layer to improve computational efficiency. The R^2 values varied between 0.8 and 0.99, depending on the country.

Fang et al. [18] developed a random forest-based model that achieved more accurate predictions of construction-stage carbon emissions, with a lower mean square error (0.7649) and an R^2 value of 0.6403. This model, which utilised data from 38 buildings, identified six influential design parameters: foundation area, above-ground area, underground area, building height, number of above-ground floors, and basement depth. The study revealed that foundation area, underground area, and building height had the most significant impact on construction-stage carbon emissions.

Interestingly, the choice of input features has a considerable effect on the suitability of machine learning methods and their outcomes. For example, in the research by Zhang et al. [5], models using only building height as a feature resulted in inadequate estimates, with R^2 values below 0.4 for embodied carbon prediction. However, when combining features such as building height, structural form, seismic fortification intensity, delivery type, geographical region, and material cost, the extremely randomised trees algorithm performed significantly better, achieving R^2 and MAPE values of 0.821 and 0.054, respectively. When additional features such as prefabrication technique and material consumption (steel, concrete, brick, and block) were considered, the XGB algorithm performed optimally, with R^2 and MAPE values of 0.917 and 0.038 on the test dataset.

In other scenarios, Cang et al. [19] 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 [9].

Su et al. [20] 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. The work considered the temporal fluctuations in occupant profiles, behaviours, and the carbon intensity of energy. In another study, Chen et al. [13] used AI, 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. To predict embodied carbon emissions in building structures during the design process, the study conducted by Pomponi et al. [21] 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.

From the above, there is an increasing trend in AI-driven building management to consider the carbon footprint of buildings, even though most research still treats operational and embodied carbon emissions separately. However, to take a more forward-looking approach, WLC assessment should be viewed as a comprehensive method for fully addressing the environmental impact of buildings' development and operation.

III. METHODOLOGY

A. *Data collection*

Two data sources were used in this study. The first was carbon related data provided by the industrial partner, consisting of 57 large building projects (each over £5 million), where the majority are educational buildings. The second source comprised cost data of a total of 1,008 samples extracted from the Royal Institute of Building Surveyors' Building Cost Information Service (BCIS) dataset.

The data from the BCIS website has been extracted using a specialised Python script developed specifically for this task. This script employs the web scraping tool Selenium to facilitate data collection and is designed to target specific information related to educational buildings, administrative offices, and residential projects; primarily the types of projects undertaken by Morgan Sindall, with residential initiatives managed by their subsidiary.

Utilising Selenium, the developed Python script dynamically interacted with the BCIS platform, navigating through the web interface, submitting queries, and extracting relevant data based on predefined filters. This setup allowed for automatic pagination, enabling the script to seamlessly traverse multiple pages to gather comprehensive information on new builds within specific categories mentioned above.

The developed script's automation capabilities ensured that each session extracted detailed information, including base date, location, floor area, building type, storeys, type of substructure, and frame type. Moreover, in cases where no data was available for a particular query, the script automatically left that entry blank. The scraped data was then written directly into a data frame, creating a structured table format that facilitated the organisation of information and subsequent analysis.

B. Data pre-processing

To ensure that predictive models receive high-quality data, data pre-processing is an essential step prior to model development. This iterative process transforms raw data into formats that are both comprehensible and practical [22]. Data pre-processing encompasses several key activities, including data cleaning, outlier removal, formatting of categorical and numerical variables, addressing missing values, and feature encoding.

In this study, data was extracted from the BCIS database to predict the overall cost of buildings based on key features, while predictions for whole-life carbon emissions were based on a previous building information dataset from Morgan Sindall. Both datasets presented challenges, including missing values, outliers, and a mixture of categorical and numerical variables.

A thorough data cleaning process was conducted in Excel, given that the experiment involved only 1,008 samples for building cost predictions and 57 buildings for whole-life carbon predictions. Statistical charts and graphs were employed to identify and remove outliers effectively, ensuring that the data remained representative and free from anomalies that could skew predictive accuracy. Additionally, natural logarithm (ln) transformation was applied to the target variable to enhance model convergence and stabilise variance, which is particularly beneficial in regression analyses.

The utilisation of domain knowledge was crucial in resolving missing values. Appropriate techniques were utilised to remove or impute these missing values, considering the context of the data. This method preserved the models' applicability to real-life scenarios while simultaneously enhancing the dataset's integrity.

In terms of feature encoding, it is vital to convert categorical variables into a format suitable for machine learning algorithms. For instance, when dealing with categorical labels such as "Category A" and "Category B," these must be transformed into numerical representations (e.g., “0” for "Type A" and “1” for "Type B") to enable effective processing by the model [22]. One-hot encoding was applied where applicable, creating binary columns for each category, thus preserving the information without introducing bias.

A popular method for validating models is data splitting, in which a given dataset is divided into two distinct sets: training and testing. Next, the training set is used to fit the statistical and machine learning models, and the testing set is used to validate them. Assessment and comparison of the predicted performance of various models can be undertaken without being concerned about potential overfitting on the training set by keeping a set of data for validation apart from the training set [23].

Alternate sampling was used to split the BCIS dataset into training and testing sets equally, utilising a 50/50 split to reduce overfitting. The two sets of samples were alternated, and it was discovered that this strategy worked well. While maintaining a sizable and representative dataset for assessment, it made sure the model was exposed to a wide variety of situations during training. This method achieved a compromise between the requirement for a large training set and the capacity to objectively evaluate the model's generalisation capabilities. An 80/20 split which is commonly used [23] for the whole-life carbon estimates, meaning that 80% of the data was set aside for model training and 20% for testing. This ratio is frequently employed to maintain enough data for training while offering a fair evaluation of the model's performance.

After the data was split into training and testing, data augmentation techniques were used on the training samples. Augmentation is an approach which generates new data examples for model training thereby increasing dataset size and improving model generalisation and robustness to make up for the small dataset size [24]. This approach ensures that models work effectively on real-world data and helps reduce overfitting, making it especially helpful for small or imbalanced datasets. Data augmentation has gained widespread acceptance in the machine learning community when used in an ethical manner and proven to improve performance.

To enhance the robustness and size of the training datasets, a systematic data augmentation technique was employed. In addition to the original training samples, additional training samples were generated by augmenting the actual values. For each original data point, new samples were created by adding small increments of 0.1%, 0.2%, and 0.3% of the actual value to the original values. This method effectively increased the diversity of the dataset without the need for new data collection. The augmentation strategy, not only expanded the training set, but also contributed to improved model generalisation and reduced risk of overfitting, ultimately leading to more reliable model performance on unseen data.

Overall, this meticulous approach to data pre-processing laid a solid foundation for accurate predictions of both building costs and whole-life carbon emissions. By addressing the complexities inherent in the datasets and leveraging domain knowledge, the study aimed to produce models that are not only statistically sound but also aligned with industry practices and sustainability goals.

C. *Feature Selection*

Feature selection was conducted using a filter-based method that are based on statistical measure to make sure the model can be more transparent. Nevertheless, when it comes to correlation analysis, it is a widely used method for selecting features from continuous variables. It is not appropriate for categorical data and specifically suited for linear relationships and is a univariate approach [25].

Fig. 2 presents the correlation heatmap which reveals significant relationships between several key building features. The analysis shows that all variables are positively correlated. The WLC shows strong correlations with all other variables, particularly with the gross internal area (GIA) at 0.89 and the net internal area (NIA) at 0.88, which are established metrics for cost and building efficiency. Therefore, when predicting WLC, it is essential to consider all these factors.

On the other hand, Elastic Net is suited for continuous target variables and can effectively handle feature sets that include both numerical and categorical variables.

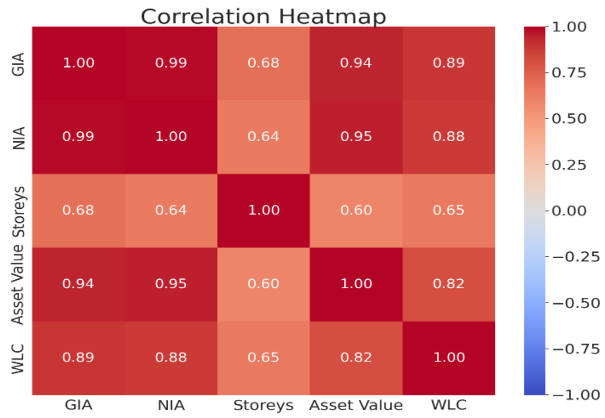

Fig. 2. The correlation heatmap of the data

This approach serves as a linear regression model that combines the characteristics of Lasso regression (L1 regularisation) and Ridge regression (L2 regularisation). By simultaneously applying L1 and L2 regularisation, Elastic Net achieves feature selection while stabilising the model's predictive performance [9]. Its advantage lies in the ability to shrink unimportant feature coefficients to zero and mitigate the effects of multicollinearity through L2 regularisation, thereby balancing the sparsity and stability of the model.

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Based on the results as shown in Fig. 3Fig. 3 of feature selection using Elastic Net, it can be seen that the importance of building features as follows: the size and value of the building appear to be the most critical predictive factors. Among these, the gross internal area (GIA) and net internal area (NIA) demonstrate the strongest positive influence, indicating that the size of the building is a primary indicator for predicting the target variable. Following closely are asset value and the number of floors, both of which also show significant positive impacts. These findings highlight the importance of the physical characteristics and economic value of the building in predictive models.

The influence of the primary cooling type surpasses that of heating and ventilation systems, which may reflect certain aspects of energy patterns. Interestingly, while building type is important, its impact is not as pronounced as the GIA or NIA value and suggests that when considering building type.

Secondary system types, such as secondary cooling, heating, and ventilation systems, have a relatively minor impact on the target variable. This may indicate that the characteristics of primary systems are more critical than those of backup or auxiliary systems when assessing or predicting building performance. Overall, these results indicate that when analysing or predicting building-related target variables, priority should be given to the size, value, and fundamental structural features of the building. While environmental control systems do play a role, their importance seems secondary to the core physical characteristics of the building.

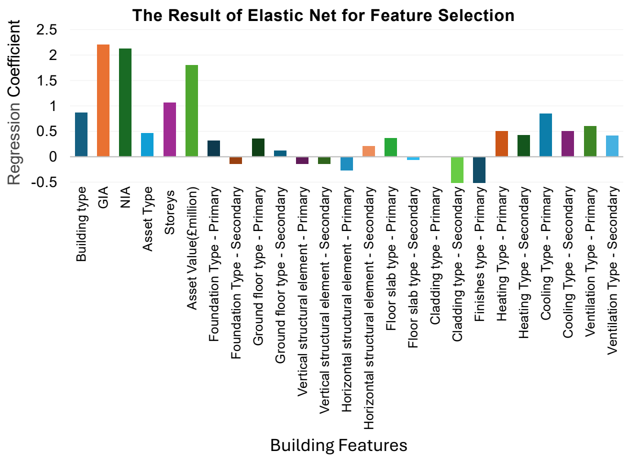

Fig. 3. The use of Elastic Net for feature selection

These insights could have significant implications for fields such as building design or energy efficiency planning. However, the potential correlations between features when interpreting these results should also be cautiously considered, as the Elastic Net model may distribute importance among related features. However, this result shows that the cooling system have a significant impact on the whole life carbon emissions which is seldom mentioned in the literature.

Additionally, an expert knowledge approach was integrated into the feature selection process, allowing domain expertise to guide the identification of relevant features based on theoretical understanding and practical experience. This comprehensive strategy ensured a well-rounded selection of features that enhances model performance. Therefore the features selected for this regression tasks are: GIA, NIA, storeys, cost of the building (asset value), building type and cooling, heating, ventilation system.

In summary Fig. 4 and Fig. 5 illustrate the process of selecting the dominant features for whole life carbon and cost prediction.

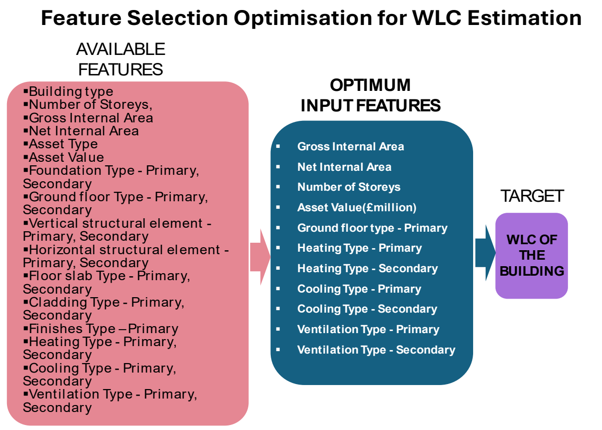

Fig. 4. Optimisation of input features for Whole Life Carbon prediction

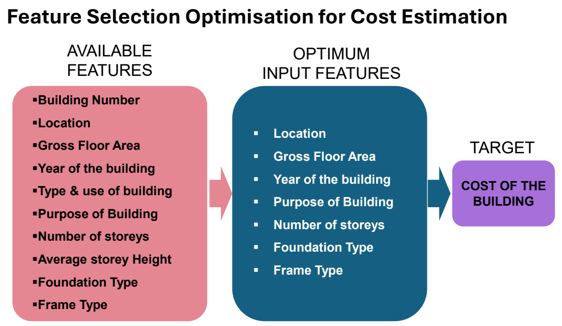

Fig. 5. Optimisation of input features for building cost prediction

D. Architecture of the neural network

Model training is an important step in developing any predictive model, particularly when using neural networks due to their ability to capture complex patterns and relationships within the data. Neural networks were chosen for this task because of their flexibility and power in modelling non-linear relationships, especially when the input-output mapping is intricate and multi-dimensional.

A feedforward neural network model was used in this study to predict the desired outcomes. As shown in Fig. 6, the model begins with an input layer corresponding to the input features and an output layer that generates predictions. The architecture comprises three hidden layers, with neuron configurations optimised through experimentation.

The network was created using 'feedforwardnet' function, which is designed for general feedforward networks. The hidden layers are configured with the hyperbolic tangent sigmoid 'tansig' activation function, while the output layer uses the linear activation function 'purelin'. This combination allows the hidden layers to capture complex non-linear relationships in the data while ensuring that the output layer can model continuous values, which is crucial for regression tasks.

For training the model, the 'Levenberg-Marquardt' algorithm (trainlm) was chosen. It is known for its efficiency in minimising error and its ability to converge quickly, particularly in small- to medium-sized networks. This backpropagation algorithm is well-suited for neural network training due to its balance between speed and precision.

To find the optimal model setup, a variety of network configurations and training approaches were investigated through hyperparameter tuning. The number of neurons, training function, and activation functions are examples of critical hyperparameters that affect how the model learns using neural network. To ensure that the neural network successfully captures underlying data patterns and achieves higher accuracy and generalisation in predictions, this approach seeks to identify the optimal values for these hyperparameters. Different architectures were tested, including 'feedforwardnet', 'fitnet', 'patternet, and 'cascadeforwardnet'. In addition to 'trainlm' for the training function, experiments were conducted with 'trainbr' (Bayesian Regularisation) to compare performance in terms of convergence speed and accuracy. This comprehensive evaluation facilitated the identification of the most effective

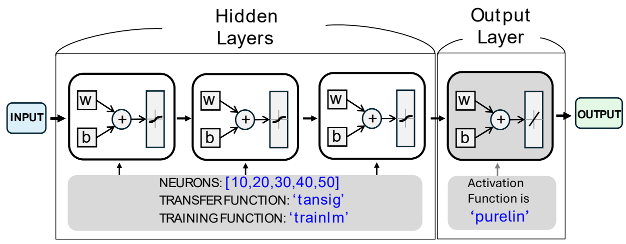

Fig. 6. The architecture of the implemented neural network

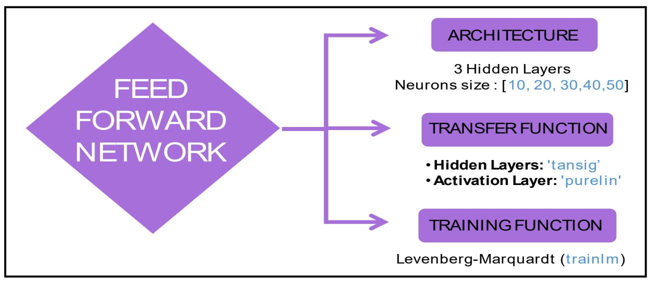

Fig. 7. The optimal configuration of the implemented neural network

configuration for the predictive model, which is shown in the Fig. 7.

In terms of the activation functions, both 'tansig' (hyperbolic tangent sigmoid) and 'logsig' (logarithmic sigmoid) were tested for the hidden layers, while 'purelin '(linear) and 'relu'

(rectified linear unit) were explored for the output layer. After extensive testing, the combination of 'trainlm' for training, 'tansig' for the hidden layers, and 'purelin' for the output layer was found to deliver the best overall performance and less Mean Average Error (MAE), providing a robust balance between learning complex patterns and avoiding overfitting.

MATLAB was used to build and train the AI model, and the final configuration consistently yielded the best results.

E. Model Training and Evaluation

Through extensive experimentation and optimisation of the network architecture and hyperparameters, this configuration was found to be effective for both the cost and WLC prediction.

The optimisation process resulted in the development of 125 neural network models, testing various configurations with neuron counts ranging from 10 to 50 in each layer.

IV. RESULTS AND DISCUSSION

In order to understand which configuration can produce better results, a for-loop is introduced to iterate through all transfer functions, training algorithms, and neural networks with 3-9 neurons, and obtain the results as shown in the TABLE I. The table outlines the performance of various training algorithms and neural networks with different transfer functions, and assessed based on MAPE and R^2 values. The five training algorithms included are trainlm, trainscg, trainbr, traingdx, and trainrp. Each algorithm has been tested using four types of neural networks: Fitnet, Cascadenet, Feedforwardnet, and Patternet.

TABLE I. PERFORMANCE COMPARISON OF NEURAL NETWORK ARCHITECTURES

Algorithm	Neural Network	Error (%)	R^2
trainlm	Fitnet	0.27	0.86
	Cascadenet	0.36	0.83
	Feedforwordnet	0.27	0.87
	Patternet	0.37	0.83
trainscg	Fitnet	0.47	0.76
	Cascade	0.83	0.72
	Feedforwordnet	0.52	0.79
	Patternet	0.47	0.74
trainbr	Fitnet	0.31	0.86
	Cascade	0.39	0.81
	Feedforwordnet	0.32	0.82
	Patternet	0.36	0.80
traingdx	Fitnet	0.85	0.74
	Cascade	111.2	0.69
	Feedforwordnet	102.99	0.76
	Patternet	0.89	0.69
trainrp	Fitnet	0.58	0.79
	Cascadenet	0.74	0.71
	Feedforwordnet	0.6	0.81
	Patternet	0.61	0.80

Under the trainlm algorithm, the neural networks exhibit relatively low MAPE difference values (0.27% to 0.37%) alongside high R^2 values (0.83% to 0.87%), demonstrating strong performance. In contrast, trainscg presents higher MAPE differences (0.47% to 0.83%) and lower R^2 values (0.72% to 0.79%), making it slightly inferior to trainlm. The results for trainbr are also favourable, with a MAPE difference of around 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'* sits in the middle, with MAPE differences ranging from 0.58% to 0.74% and R^2 values between 0.71% and 0.81%, delivering an acceptable performance but not matching the standards of trainlm and trainbr.

In summary, although trainlm and trainbr were the top performers in this test with lower MAPE and higher R^2 values, the trainlm is known for its speedy advantage due to its ability to dynamically adjust parameters, adjust weights, and accelerate convergence, making each iteration more effective. Last, the performance of traingdx was notably subpar, particularly in the Cascadenet and Feedforwardnet models.

Following the above stage, extensive training with more neurons and evaluation led to the identification of an optimal configuration for cost prediction: 10 neurons in the first hidden layer, 40 neurons in the second hidden layer, and 50 neurons in the third hidden layer. This configuration achieved a mean absolute error (MAE) of 1.12% indicating a strong predictive capability, with a training time of 37 seconds.

For WLC prediction, a different configuration of 30 neurons in the first hidden layer, 30 neurons in the second hidden layer, and 20 neurons in the third hidden layer was used, resulting in an MAE of approximately 3.53 with a training time of 14 seconds.

The error distribution graph (Fig. 8) displays the percentage error across predictions for whole life carbon (WLC).

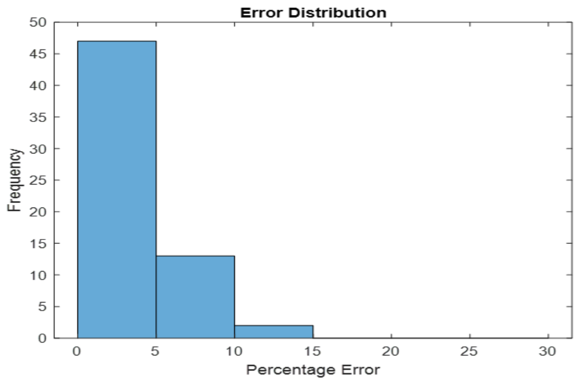

Fig. 8. Histogram of error distribution for WLC prediction

The majority of errors are concentrated between 0% and 5%, indicating high accuracy in the model's predictions and suggests that the model is reliable.

TABLE II. BEST RESULTS FOR COST PREDICTION

Layer 1	Layer 2	Layer 3	MAE	Time
50 Neurons	50 Neurons	30 Neurons	1.12 %	37 sec
10 Neurons	40 Neurons	50 Neurons	1.37 %	77 sec
40 Neurons	40 Neurons	40 Neurons	2.39 %	52 sec

TABLE III. BEST RESULTS FOR WHOLE LIFE CARBON (WLC) PREDICTION

Layer 1	Layer 2	Layer 3	MAE	Time
30 Neurons	30 Neurons	30 Neurons	3.53 %	14 sec
40 Neurons	20 Neurons	20 Neurons	3.71 %	17 sec
20 Neurons	40 Neurons	40 Neurons	4.16 %	45 sec

Error! Reference source not found.and TABLE III. present few examples of the most effective prediction results for Cost and WLC.

Furthermore, the testing of actual values graph (Fig. 9) compares expected versus predicted values for a series of samples. The close alignment between the red and blue lines demonstrates the model's effectiveness in capturing the actual data trends. The slight deviations observed in some samples fall within an acceptable range, reinforcing the model's robustness.

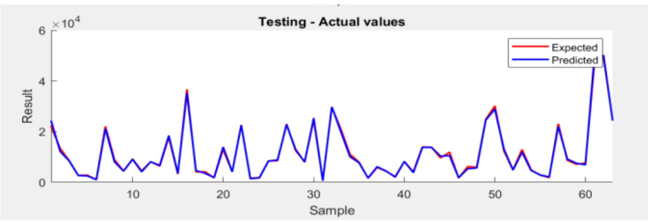

Fig. 9. Testing the neural network, results of the expected vs predicted values

Together, the above graphs highlight the model's strong predictive performance and its applicability in forecasting accurate trend representation make it a valuable tool for strategic planning and decision-making in sustainability efforts.

V. Conclusion And Future Work

This study has reviewed and assessed the implementation of AI in the built environment sector and has found that AI algorithms have the potential to enable the estimation of WLC and costs of construction projects; and therefore to be integrated into the existing carbon optimisation and evaluation software such as CarboniCa.

The conceptual AI integration approach proposed in this study is currently under development, with the next phase being industrial testing and validation of model efficacy. It is expected that the AI engine will provide an option within the CarboniCa software environment for rapid assessment of WLC based on learning from past projects and the experience of experts. Although there are slightly more than 50 recent projects, generalisability issues may arise. But since the dataset includes many education-based projects, the outcomes will specifically be suitable to the education sector. For future development, the multi-objective optimisation will be considered to enhance the carbon reduction potential of the software by providing design recommendations that are dynamic and responsive to carbon, time and cost considerations. This will lead to data-driven decisions that maximise quality and speed by leveraging past projects' data. The broader implication is that further research to develop, test and integrate the proposed AI model into existing CarboniCa software will ultimately provide practical use cases for the adoption and integration of AI in the construction industry and construction organisations; This includes, for example, solutions to improve the sustainable performance of building projects as part of net zero ambitions. However, there is still room for further experimentation in AI. For example, according to the literature review, there are other factors such as region, WWR, and local economic factors that have not yet been taken into account and can be focused on in future studies.

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