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International Journal of Earthquake Engineering
Anno XLIII - Num. 1 - 2026

BIM-Assisted Artificial Intelligence Carbon Modeling for Green and Low Carbon Building Designs

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SUMMARY: *Nowadays, climate change has become a serious issue for the world, and the creation of low-carbon green buildings becomes one of the ways offered by humans to overcome the existing problems. In this research, through BIM technology, inventory data and emission data from selected buildings have been collected. With correlation analysis and elastic net algorithm, design features affecting building carbon emissions have been screened out, and 8 features were regarded as predictors. Then, an improved gray wolf optimization algorithm-based support vector machine method (IGWO-SVM) is utilized to establish the prediction model of building carbon emissions. Through model comparisons, it has been found that our IGWO-SVM model has attained an* R^2 *value of 0.811, which is 9.45% to 125.91% better than other models, while the metrics of RMSE, MAE, NRMSE, and CV(RMSE) have reached the lowest values compared to other models with at least 12.26% lower performance. It will help architects estimate carbon emissions accurately, enabling green and low-carbon buildings to be promoted.*

KEYWORDS: *BIM technology; Grey Wolf Optimization Algorithm; Support Vector Machine; Carbon Emission Prediction; Architectural Design*

1 Introduction

As per the findings of the Intergovernmental Panel on Climate Change (IPCC), carbon emissions globally have been increasing continuously, and there are still serious problems with climate governance, demanding immediate and effective measures for carbon emissions reduction [1]. By 2024, the emission of carbon in the building and construction industry will be up to 5.08 billion tons of CO2, which occupies 36% of global carbon emissions [2]. In such a scenario, the efforts at reducing emissions made by the construction industry, particularly the adoption of green and low-carbon buildings, become very significant.

Green and low-carbon buildings are the outcome of a perfect blend between environmental protection and sustainability in the construction sector. They have helped to improve energy efficiency, minimize the effect of buildings on the environment and proved to be effective in reducing CO2 emissions in response to global climate changes with the help of “low-carbon” approach [3-6].The green buildings follow all green environmental standards for materials, utilize water resources effectively and improve the quality of the internal environment to create comfortable conditions. These buildings include not just buildings themselves but also the entire system of ecological functions both in and outside buildings, as well as systems that ensure community safety and stability [7-10]. In order to reduce the amount of energy used by the construction sector, energy management systems can be employed along with the use of

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https://doi.org/10.65102/is2026128

Published: 30 April, 2026

energy-efficient insulating techniques as well as developments in renewable energies [11-13].

Carbon emission models play a vital role in solving the climate change problem. In order to construct an efficient carbon emission model, one should make a thorough evaluation of various aspects, guaranteeing the accuracy of data and scientific validity of the model as well as feasibility [14-16]. Thanks to the achievement of the “dual carbon” goal, many countries have enacted relevant policies on low-carbon construction. Building carbon emissions accounting has gradually shifted from voluntary to mandatory compliance, driving continuous innovation in green and low-carbon building technologies. This has facilitated the integration of intelligent technologies into carbon management, where they play a vital role [17-19]. Utilizing intelligent technologies for carbon emission modeling enables the quantitative analysis of greenhouse gas emissions from human activities, providing scientific basis for policy formulation and technological optimization [20, 21]. The integration of Building Information Modeling (BIM) technology with Artificial Intelligence (AI) charts a new course for the construction industry, vigorously advancing its low-carbon transformation and guiding the optimization of carbon emissions in green, low-carbon building design.

BIM technology, because of its visualization, coordination, simulation, optimization, information completeness, parameterization, integration and chartability, runs through the whole life cycle of the building, carries out comprehensive management of the whole process and elements of the building, and is able to realize the integration and shared transmission of building information and provide the basis for scientific decision-making for all the parties [22-25]. In the field of construction, BIM technology shows significant advantages in optimizing design, improving construction efficiency, enhancing collaboration, accurate budgeting and improving safety, effectively helping to build green and low-carbon building design. Literature [26] utilized two BIM tools and an energy simulation tool to construct an effective technological framework for conveying building information to simulate energy consumption in building operations, and allowed for sensitivity analysis of parameters in building operations. Literature [27] explored the role of BIM technology for carbon emission assessment in green prefabricated buildings in the form of modeling, simulation and analysis to analyze the structural components and assembly process to understand the energy consumption and depletion. Literature [28] established a performance-integrated BIM architecture for optimizing energy efficiency and environment throughout the building lifecycle, promoting indoor environmental quality, reducing costs, and facilitating data-driven green building design. Literature [29] used 3D BIM and averaging index method for energy analysis of a hospital building model to achieve environmentally sustainable support with BIM adjustments of different parameters and components in the building project, including design process optimization, energy cost savings, and reduction of carbon dioxide and electricity consumption. Literature [30] used an unmanned aerial vehicle (UAV) to acquire digital images of the building site and generated a 3D building parameter model in Meshroom to assess the energy consumption and CO2 emissions of a traditional building retrofitted to a green building using BIM. Literature [31] explores the association between material properties and building configuration with the analysis of materials in the life cycle of green building design based on BIM tools, where not only the design review but also the support of embedded energy and carbon footprint assessment of building materials are given in such tools to support sustainability in terms of materials for green building design.

Artificial intelligence technologies are gradually changing the traditional paradigm of building energy efficiency. Literature [32] stated in an evaluation study that AI can contribute to the popularization of zero-energy buildings, reduction of cost premiums, and improvement of high energy efficiency levels in the building sector, and it is expected that energy consumption and carbon emissions under AI applications in the building sector will be reduced by about 8% to 19% in 2050. Literature [33] uses AI's image recognition technology and optical sensor technology to monitor the external light fluctuation and extract the indoor light intensity of a low energy-consuming building, respectively, and combines it with big data analysis to dynamically adjust the building's heating and cooling system to optimize thermal energy use. Literature [34] designed an AI technology for smart building monitoring system to optimize energy consumption and utilization under an environmentally friendly design monitoring system by predicting energy consumption, producing and recovering the energy required for building assessment. Literature [35] adopted an explainable artificial intelligence (AI) technique for forecasting building energy consumption and green house gas emissions by considering building features and building form in terms of building geometry and urban morphology. Literature [36] innovated machine learning for estimating the initial cost required for green buildings (no net energy consumption type) and estimating the electricity consumption of buildings under soft computing methods and data decomposition towards zero-energy and low-carbon buildings. Literature [37] describes AI-based renewable energy systems for buildings, which can expand the range of renewable energy and carbon reduction measures for buildings without the need to rebuild infrastructure, and have good adaptability under changes in technology and strategy to promote sustainable and carbon-neutral buildings. Literature [38] applies genetic algorithms to optimize building parameters for building energy consumption, natural lighting and natural ventilation to enhance and balance energy efficiency and occupant comfort. Literature [39] performed schematic design of reinforced concrete building structures, used carbon emission assessment based on secondary projects for detecting carbon-intensive structural components, and incorporated genetic algorithms to optimize components with design constraints, thus achieving low-carbon design optimization of building structures.

Currently, multi-technology integration covering AI and BIM is applied to carbon and building energy management. Literature [40] analyzed the application of GIS, BIM, remote sensing, and AI in facilitating net-zero carbon in cities, and suggested the use of AI and big data analysis to monitor the time required for cities to achieve net-zero carbon, and the use of GIS and BIM to estimate the physical carbon emissions of the city and to predict the emissions from urban development. Literature [41] adopts both AI techniques and Building Information Modelling (BIM) in order to create a predictive model based on the operation data of HVAC for optimizing indoor low-carbon environments. Literature [42] shared a 3D integrated application based on machine learning (carbon footprint estimation), large-scale language modeling (generating building design optimization recommendations) and BIM technology, combined with the development of a life cycle assessment tool to assist architects in achieving low-carbon building design. In literature [43], the integration of enhanced genetic algorithm models and BIM was carried out to optimize the design of green buildings through optimization of the carbon emissions measurement and the green building assessment throughout the entire life span of the building, as well as through analysis and assessment of energy use, to identify the relationship between the two factors and optimize the design parameters. Literature [44] introduced digital twin technology based on IoT, BIM and BIM for predictive monitoring of carbon dioxide equivalents produced by existing buildings and visualizing the relevant data in an interactive dashboard. Literature [45] presents a framework based on the digital twin technology with the combination of BIM and remote sensing imaging processing for the estimation of carbon emissions and carbon reduction in the operation stage of the building.

The study investigated 70 building cases, employing the emission factor method to quantify carbon emissions from the case buildings. The BIM technique was employed to support data collection, followed by a discussion of the research outcomes. Following this basis, the DesignBuilder software simulation was undertaken to investigate the effect of the factors during the design phase of the architecture on building carbon emissions. The variable selection was further carried out using correlation analysis, collinearity analysis, and elastic net regression. To enhance the predictive accuracy of the SVM model, the Grey Wolf Optimization algorithm was introduced for model optimization. Using the selected architectural design factors as input features, a building carbon emissions prediction model was constructed. Finally, PCR, RF, and MLP were employed as comparison methods. The R^2, RMSE, MAE, NRMSE, and CV(RMSE) metrics of the proposed model were compared with those of the reference models to evaluate the performance of the IGWO-SVM model for building carbon emissions prediction.

2 BIM-Based Carbon Emissions Data Collection

2.1 Building Carbon Emissions Data Survey

To collect architectural data on different building types across various climate zones, a survey of 70 building case studies will be conducted from October 2024 to May 2025. Residential and public buildings will be selected from cold climates and hot-summer/cold-winter climates.

2.2 BIM-Based Quantity Surveying Methods

2.2.1 Building Carbon Emissions Measurement

(1) Content of the Measurement List

The analysis content and process of the measurement list are shown in Figure 1. For the construction phase, drawing on methods from construction project estimates and budgets, the list proposes using building sub-projects and measures as basic units, and researches corresponding “comprehensive carbon emission coefficients.” For the building operation phase, since carbon emissions ultimately stem from equipment energy consumption, building equipment serves as the basic measurement unit, with appropriate consideration given to building repairs and upgrades.

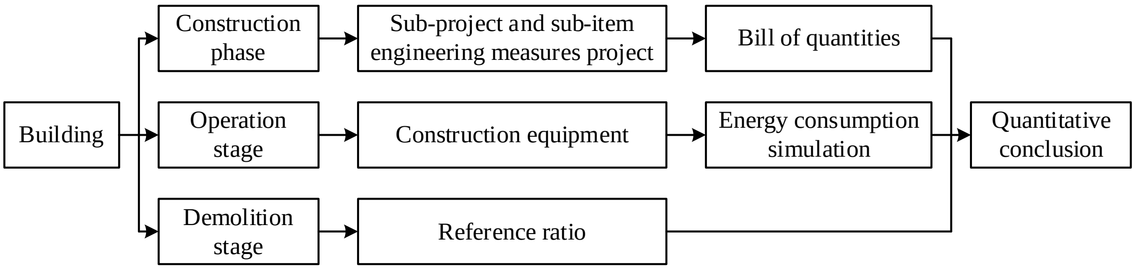


Figure 1: The inventory analysis content and process

(2) Calculation Formula

According to the ways of acquiring carbon emissions data, the calculation of carbon emissions in the entire life cycle of a building mainly includes three methods, which are the direct measurement method, material balance method, and emission factor method. In the emission factor method, total carbon emissions will be calculated by the average amount of carbon emitted per unit of product in normal conditions.

Synthesizing the preceding research, the formula for calculating a building's life cycle carbon emissions is:

$$E_{total} = E_{cons} + E_{occup} + E_{disp} \tag{1}$$

Among these, E_{total} represents the predicted carbon emissions over the building's entire lifecycle. E_{cons} denotes the generalized carbon emissions from construction, accounting for building material recycling and disposal, as well as maintenance of building components. E_{occup} reflects the generalized carbon emissions during the operational phase, considering both the equipment itself and energy consumption. E_{disp} represents the carbon emissions from construction demolition. — construction carbon emissions during the building demolition phase.

The formula for calculating carbon emissions during the building construction phase is:

$$E_{cons} = \sum_{i=1}^{n} C_i \times m_i + \sum_{j=1}^{k} C_j \times m_j \tag{2}$$

where, i — sequence number of the sub-item, C_i — comprehensive carbon emission coefficient for the ith sub-item (kgCO₂/unit), m_i — quantity of the ith sub-item (unit), j — the measure item sequence, C_i — the comprehensive carbon emission coefficient for measure item j (kgCO₂/unit), m_j — the quantity of measure item j.

The carbon emission calculation formula for the building operation phase is:

$$E_{occup} = \sum_{i=1}^{n} E_i \tag{3}$$

where i represents the i-th building equipment item, including HVAC systems, lighting systems, etc., and E_i denotes the carbon emissions of the i-th building equipment item.

Carbon emissions during the building demolition phase are calculated as 10% of the construction phase mitigation measures.

2.2.2 Carbon Emission Factors

(1) Energy Carbon Emission Factor

The energy carbon emission factor is the quantity of greenhouse gases produced per unit weight of energy utilized, acting as an important factor in defining the greenhouse gas emissions associated with that particular energy resource.

The method of BIM was used for data collection purposes, after which there is a discussion regarding the results from the research. Based on this approach, the simulation process was carried out using the DesignBuilder software application to analyze the influence of the factors during the architectural design process on the amount of carbon emitted by the building.

$$\begin{aligned} &\text{Carbon dioxide emission coefficient} \\ &= \text{Average lower calorific value} \\ &\times \text{carbon content per unit calorific value} \\ &\times \text{carbon oxidation rate} \\ &\times (44/12) \end{aligned} \tag{4}$$

Electricity: The average carbon dioxide emission factor per unit of electricity supplied is 0.801 kg/kWh.

(2) Building Material Carbon Emission Factors

The emissions from construction materials consist of three elements: emissions arising from production, negative emissions due to recycling, and emissions from waste management. Energy usage and emissions from the production of the various construction materials are presented in Table 1.

Table 1: Energy consumption and carbon emission coefficient of major building materials

Building materials	Unit	Carbon emission coefficient(kg CO_2/ unit)
Steel	kg	1.722
Steel wire	kg	2.208
Cement	kg	0.894
Concrete	m^3	551
Aerated concrete block	m^3	291
Lime	kg	1.2
Wood	m^3	73.9
Architectural glass	kg	2.91
Clay brick	Kilopron	504
Grey brick	Kilopron	459

(3) Bill of Quantities Carbon Calculation Model

The bill of quantities carbon calculation method aligns with cost estimation practices, using individual work items as the basic unit. It calculates construction-phase carbon emissions by applying comprehensive carbon emission coefficients to each work item.

(4) Comprehensive Carbon Emission Coefficient

To support the Bill of Quantities carbon calculation model, this paper introduces the concept of a “comprehensive carbon emission coefficient” for quantities. In this approach, “carbon” is treated as a currency, analogous to the comprehensive unit price in pricing models.

The formula for calculating the comprehensive carbon emission coefficient C_i for a sub-project is:

$$C_i = \left[\sum pC_{per} + \sum qC_{mat}(1-\mu) + \sum rC_{mach}\right](1+\eta) \tag{5}$$

Among these, p,q,r represent the quantities of labor, materials, and machinery in various unit projects, respectively; $C_{pe}, C_{mat}, C_{mach}$ denote the carbon emission coefficients for labor, materials, and machinery, respectively; μ is the material recovery rate. In this paper, it has been incorporated into the material carbon emission coefficient. η represents the maintenance rate of building components, i.e., the average proportion of replacements required for a component over its building lifecycle. Due to research limitations, this factor is not considered in this study.

The formula for calculating the comprehensive carbon emission coefficient C_j of a measure item is:

$$C_j = \sum pC_{per} + \sum qC_{mat} + \sum rC_{mach} \tag{6}$$

where p,q,r represent the quantities of labor, materials, and machinery in various unit projects, respectively, and $C_{pe}, C_{mat}, C_{maxh}$ denote the carbon emission coefficients for labor, materials, and machinery, respectively.

2.2.3 BIM-Based Bill of Quantities Data Acquisition

(1) Construction Phase Bill of Quantities Data

Carbon emissions during the building construction phase are calculated using the bill of quantities method. Therefore, BIM technology enables real-time quantification of construction quantities during the design phase. Combined with comprehensive carbon emission practices, this allows calculation of the building structure's carbon emissions. For carbon emissions from construction phase measures, BIM's 4D construction simulation can be employed. By utilizing Navisworks to extract foundational data related to carbon emissions and leveraging carbon emission assessment software, carbon emissions during the construction phase can be calculated.

(2) Operational Phase Inventory Data

The carbon emissions from the operations stage of buildings can be traced back to the usage of energy in the form of power consumed by the HVAC and lighting equipment. Hence, using an elaborate BIM, the load for various stages like air conditioning, lighting, etc., can be calculated in order to procure the right type of equipment. Using information about the operations stage of the building, BIM can help determine the carbon emissions.

2.3 Analysis of Research Findings

Through the BIM-based measurement methodology, the building cases are mostly found in cold climate zones and hot-summer-cold-winter climate zones. The number of residential buildings and public buildings are almost equivalent in each climate zone and thus comparison between the two can be made effectively. In cold climate areas, the number of residential buildings is 16 and the number of public buildings is 20 whereas in hot summer cold winter climate areas, the number of residential buildings is 15 and the number of public buildings is 19 respectively.

Carbon emissions distribution of public buildings and residential buildings per each climate zone is presented in figure 2, where “a” represents cold climate zones while “b” represents hot summer/cold winter climate zones. The analysis revealed that the intensity of carbon emissions by public buildings in cold climates was found to be 3.34 times that of residential buildings, whereas in hot summer cold winter climates, it was found to be 2.57 times that of residential buildings. The key difference between the two types of buildings is that public buildings work longer and therefore consume more energy than residential buildings. Therefore, public buildings are a key focus in building carbon reduction research.

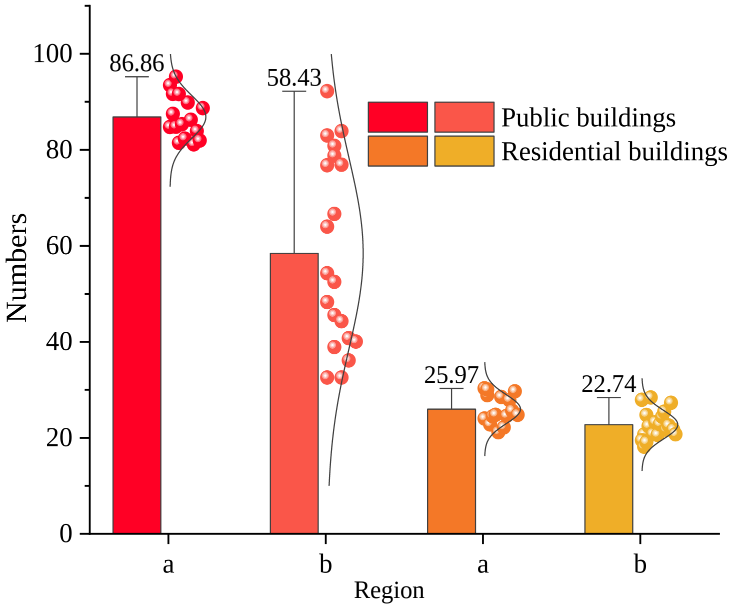


Figure 2: Distribution of carbon emissions in different climatic areas

3 Variable Selection for Carbon Emission Prediction Models

3.1 Elastic Network

Elastic Net regression combines the penalty terms of ridge regression and LASSO in its general formula.

(1) Ridge Regression

Ridge regression adds a penalty function to the least squares method. By increasing the penalty term, it introduces a bias value to the regression, thereby reducing prediction error. The expression is as follows:

$$f(w)=\frac{1}{2m}\sum_{i=1}^{m}\left[(y_i-x_i^T w)^2+\lambda_2\sum_{j=1}^{n}w_j^2\right] \tag{7}$$

Adding the sum of squared coefficients to the formula reduces the coefficients of X. If a variable has a minor impact on the effect, its coefficient can approach zero.

(2) LASSO

Similar to ridge regression, LASSO compresses coefficients by adding a penalty term, making it an effective compression estimator. Sometimes, LASSO regression is referred to as L_1 regularization for linear regression, while ridge regression is called L_2 regularization. The distinction lies in the type of regularization term used. Its objective function is:

$$f(w)=\frac{1}{2m}\sum_{i=1}^{m}\left[(y_i-x_i^T w)^2+\lambda_1\sum_{j=1}^{n}|w_j|\right] \tag{8}$$

(3) ElasticNet Regression

ElasticNet generates a regression model influenced simultaneously by both the L_1 norm and the L_2 norm. This effectively shrinks coefficients and sets some to zero. Thus, ElasticNet regression is a hybrid of LASSO and ridge regression—a linear regression model that simultaneously uses both L_1 and L_2 priors as regularization matrices. The ElasticNet algorithm can handle datasets that have multiple irrelevant variables but still provides properties of regularization. The ElasticNet algorithm will work fine when multiple variables correlate with one variable. This technique will help to get rid of irrelevant variables just like LASSO. The objective function of ElasticNet regression incorporates both L_1 and L_2 regularization terms:

$$f(w) = \frac{1}{2m}\sum_{i=1}^{m}\left[(y_i - x_i^T w)^2 + \lambda_1\sum_{j=1}^{n}|w_j| + \lambda_2\sum_{j=1}^{n}w_j^2\right] \tag{9}$$

3.2 Impact of Architectural Design Factors

3.2.1 Architectural Design Factors

This study explores architectural design parameters, which include both building form and building envelope structure. The former consists of building form ratio and building orientation, while the latter includes the thermal transmittance values of the building's external walls, roof, and window walls.

As a case study, an office building will be considered. In a cold climate region, the building has a gross floor area of 1,450 square meters and has a structure height of five floors, utilizing a frame-shear wall construction method. Based on the office building, the effects of changing design parameters on carbon emissions will be explored. DesignBuilder will be used to find the carbon emission values of the office building.

3.2.2 Analysis of Simulation Results

The results of simulation for design parameters of buildings affecting the carbon footprint of buildings are illustrated in Figure 3, where (a) through (g) represent the results of simulations for the form factor of buildings, building orientation, heat transfer coefficient of exterior walls, heat transfer coefficient of exterior windows, shading coefficient of exterior windows, heat transfer coefficient of roofs, and window-to-wall ratio of buildings, respectively.

(a) There is a rough linear relationship between the carbon emissions of buildings and building form factor. With each 0.01 increment in the form factor, the carbon emission intensity increases by about 0.65 $kgCO_2/a\cdot m^2$. Form factor has a significant impact on the carbon emissions of buildings.

(b) The orientations chosen were true south (0°), south-east 30° (30°), south-east 60° (60°), south-west 30° (-30°), and south-west 60° (-60°). Of these orientations, the southward orientation showed the least carbon emissions, which was 74.27 $kgCO_2/a\cdot m^2$. For every 30-degree deviation from south, carbon emission intensity increased by approximately 2 $kgCO_2$/a·m2.

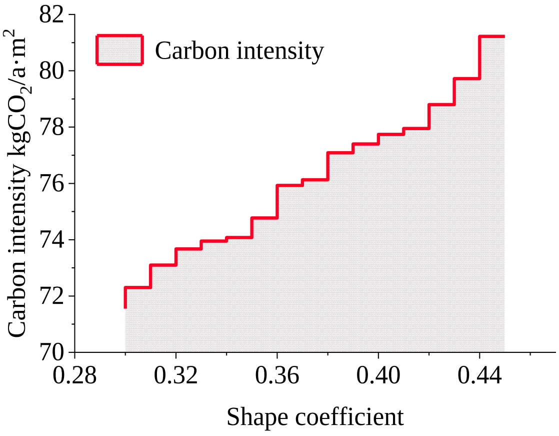
(c) When the thermal transmittance coefficient of exterior walls varies linearly, building carbon emissions do not change linearly. Overall, exterior wall thermal transmittance correlates positively with building carbon emissions.

(d) An increase of approximately 1 $W/(m^2\cdot K)$ in the thermal transmittance coefficient of exterior windows corresponds to an increase of about 2 $kgCO_2/a\cdot m^2$ in building carbon emission intensity. Overall, building carbon emissions correlate positively with exterior window thermal transmittance.

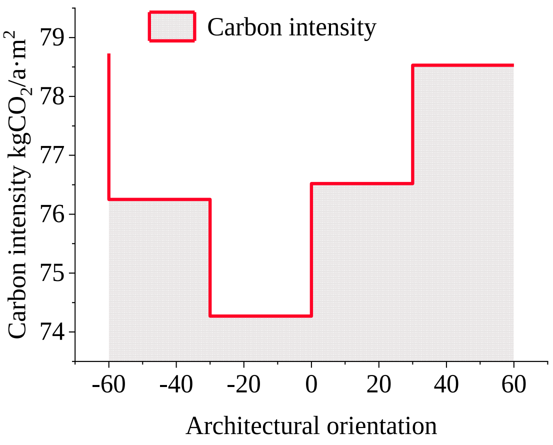
(e) Building carbon emissions decrease as the external window shading coefficient increases.

(f) An increase of approximately 0.1 W/(m^2·K) in the roof thermal transmittance results in a 0.992 kgCO$_2$/a·m^2 increase in building carbon emission intensity. The roof thermal transmittance is positively correlated with building carbon emissions.

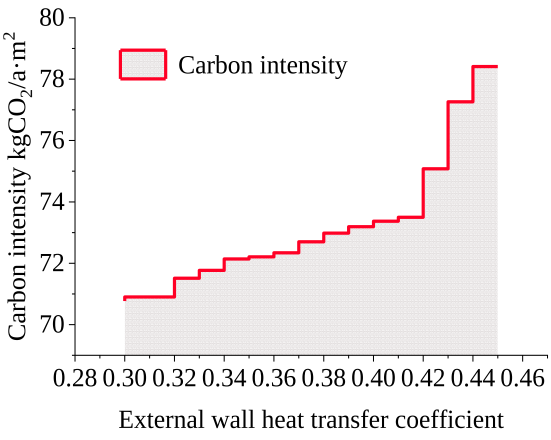
(g) For every 10% increase in the window-to-wall ratio, building carbon emissions increase by 2.34 kgCO$_2$/a·m^2. Building carbon emissions increase as the window-to-wall ratio increases.



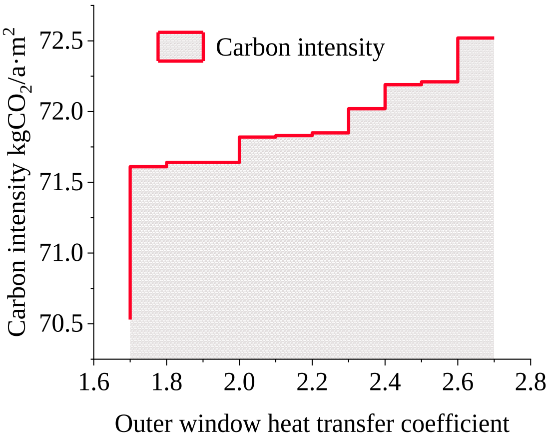
(a)Shape coefficient



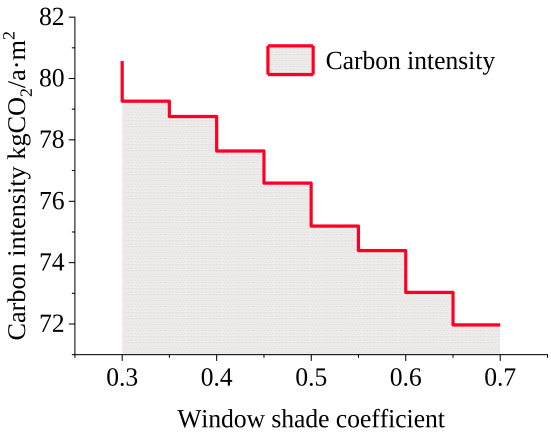
(b)Architectural orientation



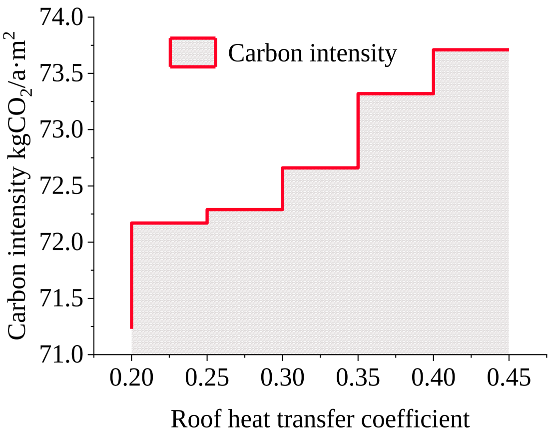
(c)External wall heat transfer coefficient



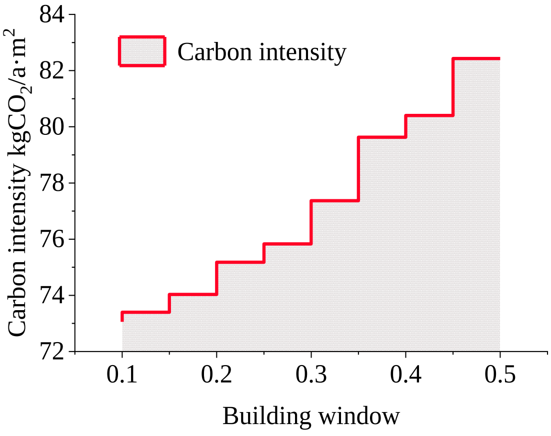
(d)Outer window heat transfer coefficient



(e)Window shade coefficient



(f)Roof heat transfer coefficient



(g)Building window

Figure 3: The impact of architectural design factors on the carbon emissions of buildings

3.3 Correlation Analysis and Variable Selection

3.3.1 Correlation Analysis

Design parameters in the survey data were numbered as X1 to X10, corresponding to the building shape coefficient, building orientation (true north orientation is 0), average exterior wall thermal transmittance coefficient, average roof thermal transmittance coefficient, exterior window thermal transmittance coefficient, exterior window solar heat gain coefficient, south-facing window-to-wall ratio, north-facing window-to-wall ratio, west-facing window-to-wall ratio, and east-facing window-to-wall ratio.

A correlation analysis was carried out on the case study building data to find the influence of various parameters together on building carbon emissions. Correlation analysis among the variables is depicted in Fig. 4. The most correlated parameter among all other parameters affecting building carbon emissions was the exterior wall heat transfer coefficient (X3), whose correlation with Y was -0.546. The least correlated variable with building carbon emissions (Y) was the south-facing window-to-wall ratio (X7), which had a correlation coefficient of -0.045. Since the Pearson correlation coefficient was less than 0.2, it should be excluded. The Pearson correlations between other variables and building carbon intensity ranged between 0.2 and 0.5, indicating moderate correlations.

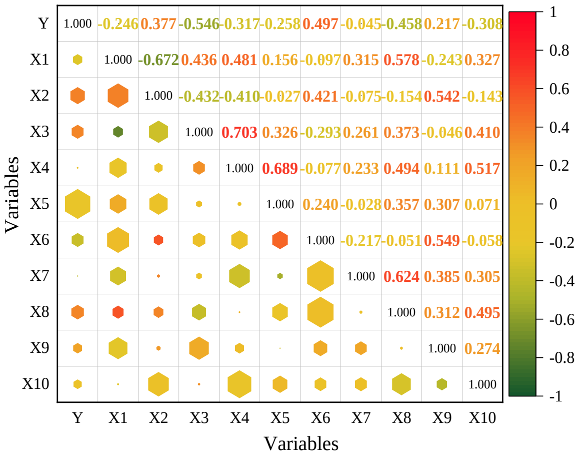


Figure 4: correlation analysis

3.3.2 Collinearity Diagnosis

It is easy for multicollinearity to cause overfitting in regression analysis, thus making the model less accurate and more difficult to interpret. Multicollinearity checks have to be done in order to avoid such problems. There are basically two types of criteria that are used in the multicollinearity check process. These include eigenvalues and condition numbers. The multicollinearity diagnosis results, as shown in Figure 5, meet the criteria for multicollinearity. Among the initially selected 10 predictor variables, multicollinearity issues exist. Further screening of predictor variables is required to enhance model quality.

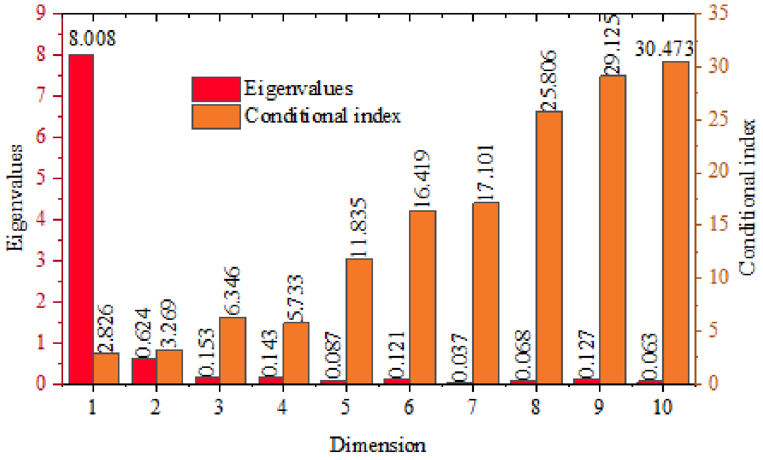


Figure 5: Collinearity diagnosis results

3.3.3 Resilient Network Analysis

Elastic net is an effective method for handling data with multicollinearity. Using SPSS software, an elastic net model was constructed for the survey data. After 200 iterations, the optimal model was obtained, with a ridge regression penalty coefficient of 0.35 and a lasso penalty coefficient of 0.07. The elastic net regression coefficients are shown in Figure 6. The coefficients for external window shading coefficient (X6) and south-facing window-to-wall ratio (X7) were 0.000, indicating they should be removed from the predictor variables. Therefore, this study selected the remaining 8 design parameters as predictor variables.

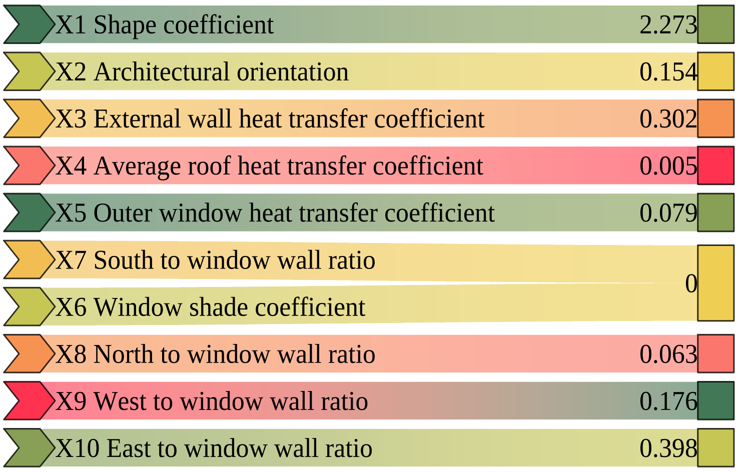


Figure 6: Elastic network regression coefficient

4 Development of the IGWO-SVM Building Carbon Emissions Prediction Model

4.1 Building Carbon Emissions Prediction Model

This paper applies Support Vector Machines (SVM) to building carbon emissions estimation, proposing an SVM-based building carbon emissions prediction model and optimizing it using the Grey Wolf Algorithm (GW).

4.1.1 Support Vector Machines

Support vector machines are classical algorithms for machine learning specifically developed to solve classification problems based on small samples. The basis of their classifying concept is to identify a hyperplane in the sample space which divides the two classes of data. The feature points nearest to the hyperplane are called support vectors, and the gap between the support vectors of different classes is the classification margin. In this way, we identify the hyperplane with maximum margin separation. For non-linearly separable data, the data can be mapped into a higher dimensional space using kernels. In this higher dimensional feature space, we build a linear classifier to obtain linear separation. Some commonly used kernels are:

Linear kernel: $x_i^T x_j$

Polynomial kernel: $(\gamma x_i^T x_j + \xi)^d$, where ξ is a constant term, γ scales the inner product, and d denotes the degree.

Radial Basis Function Kernel: $e^{-\|x_i - x_j\|^2}$

Sigmoidal Kernel: $\tanh(\gamma x_i^T x_j + \xi)$

This section employs the Gaussian kernel function, defined as follows:

$$K(x_i, x_j) = e^{-\gamma|x_i - x_i|^2} \tag{10}$$

SVM aims to find a separating hyperplane. The hyperplane's separation can be described by the following equation: $\omega^T x + b = 0$, where $\omega = (\omega_1, \omega_2, ..., \omega_d)$ determines the hyperplane's direction, and b is the bias term.

To find the hyperplane with maximum margin, it is necessary to find the parameters ω and b that minimize the following equation:

$$\min_{\omega,b} \frac{1}{2} \|\omega\|^2 \quad s.t. \quad y_i(\omega^T x_i + b) \geq 1, i = 1, 2, \ldots, m \tag{11}$$

Real-world data often cannot be completely linearly separated. To reduce overfitting, soft margin classification is introduced, allowing some samples to produce false positives. The parameter C coordinates the distance between support vectors and the decision plane, while ξ_i represents slack variables—the degree to which samples may deviate from the boundary. Slack variables are introduced to express the distance from the correct decision boundary corresponding to training samples, transforming the optimization problem into the following form:

$$\min_{\omega,b}\frac{\|\omega\|^2}{2}+C\sum_{i=1}^{n}\xi_i \tag{12}$$

$$s.t.\quad y_i(\omega^T x_i+b)\geq 1-\xi_i, i=1,2,\ldots,m \tag{13}$$

By transforming it into a dual problem using the Lagrange multiplier method and introducing a Gaussian kernel function, the problem is described as follows in the sample space containing n sample points $\{x_1,x_2\ldots x_n\}$:

$$\begin{aligned}&\max{}_{\alpha}\sum_{i=1}^{m}\alpha_i-\frac{1}{2}\sum_{i=1}^{m}\sum_{j=1}^{m}\alpha_i\alpha_j y_i y_j \phi(x_i)^T\phi(x_j)\\ &s.t.\quad \sum_{i=1}^{m}\alpha_i y_i=0, 0\leq\alpha_i\leq C, i=1,2,\ldots,m\end{aligned} \tag{14}$$

α_i is the Lagrange multiplier, and the decision function of SVM is:

$$f(x)=sign\left(\sum_{i=1}^{n}\alpha_i y_i K(x_i,x)+b\right) \tag{15}$$

$f(x)=1$ samples belong to the positive class, while $f(x)=-1$ samples belong to the negative class.

4.1.2 Gray Wolf Algorithm Optimization

(1) Generate initial wolf pack parameters: During the mutation process, define the search space as D and randomly generate the initial population within this space, as shown in Equation (17):

$$q_{i,j}(0)=q_{i,j}^{L}+rand(0,1)(q_{i,j}^{U}-q_{i,j}^{L}) \tag{16}$$

In Equation (16), (L,U) denotes the initial generation range of the population. To ensure population diversity, mutation, crossover, and selection are required. Each individual represents a set of SVM parameters.

(2) Update each wolf's position (i.e., SVM parameters) according to the Gray Wolf Optimization Algorithm rules. Introduce mutation operations to enhance population diversity by adjusting the range scaling ratio. The mutation operation for any individual is expressed as in Equation (17):

$$h_{i,j}(g)=q_{p1}+F(q_{p2}-q_{p3}) \tag{17}$$

q_{p1},q_{p2},q_{p3} denote three mutually independent parameters, and F represents the range scaling factor.

Individuals are randomly selected for crossover operations based on crossover probability to generate new candidate solutions. The crossover process is described by Equation (18):

$$v_{i,j} = \begin{cases} h_{i,j}(g), rand(0,1) \le CR \quad or \quad j = rand(1,n) \\ q_{i,j}(g), rand(0,1) > CR \quad or \quad j \ne rand(1,n) \end{cases} \tag{18}$$

In Equation (18), CR denotes the crossover probability.

(3) Update prey encirclement positions: Simulate the gray wolf pack's prey encirclement behavior by updating the positions of leaders and followers to approach the global optimum.

(4) Iteration check: Verify if the maximum number of generations (100) has been reached. If not, return to step (2) for further iteration; if reached, proceed to the next step.

(5) Upon iteration completion, select the individual with the optimal fitness value as the final solution—i.e., the optimal parameter combination for the SVM.

In this process, raw data is first acquired through data collection, then preprocessed, and finally used to estimate the overall building carbon emissions within the region via the optimized model.

4.1.3 IGWO-SVM Model

The carbon emission system is a complex, nonlinear system influenced by numerous factors. Some factors exhibit a high correlation with carbon emissions, while others have relatively minor effects. To address this issue, we propose constructing an improved support vector machine (SVM) prediction model. This model employs SVM for nonlinear mapping of the complex system and incorporates the global intelligence characteristics of the gray wolf algorithm.

Figure 7 shows the structure of the proposed model in this paper. Data for building the carbon emission factor are normalized and randomly segmented into two samples. After training the SVM network parameters, predictions are made using the parameters. Support Vector Machine is a type of nonlinear function approximator based on statistical learning theory, which has good generalization ability and stability. SVM can solve the problems of sample size, nonlinearity, and high dimensionality in pattern recognition classification. SVM has good nonlinear approximation capability. After processing the original data, it is mapped to high-dimensional feature space, forming a linear transformation in a lower-dimensional space. Secondly, training data is entered into the SVM network in random order. The deviation E between the network's output and the actual data is calculated. Subsequently, the network structure is optimized using IGWO-SVM. By employing the IGWO-SVM network, the evolutionary generation is maximized, or within the smallest error range, the absolute percentage mean of the test case set is determined.

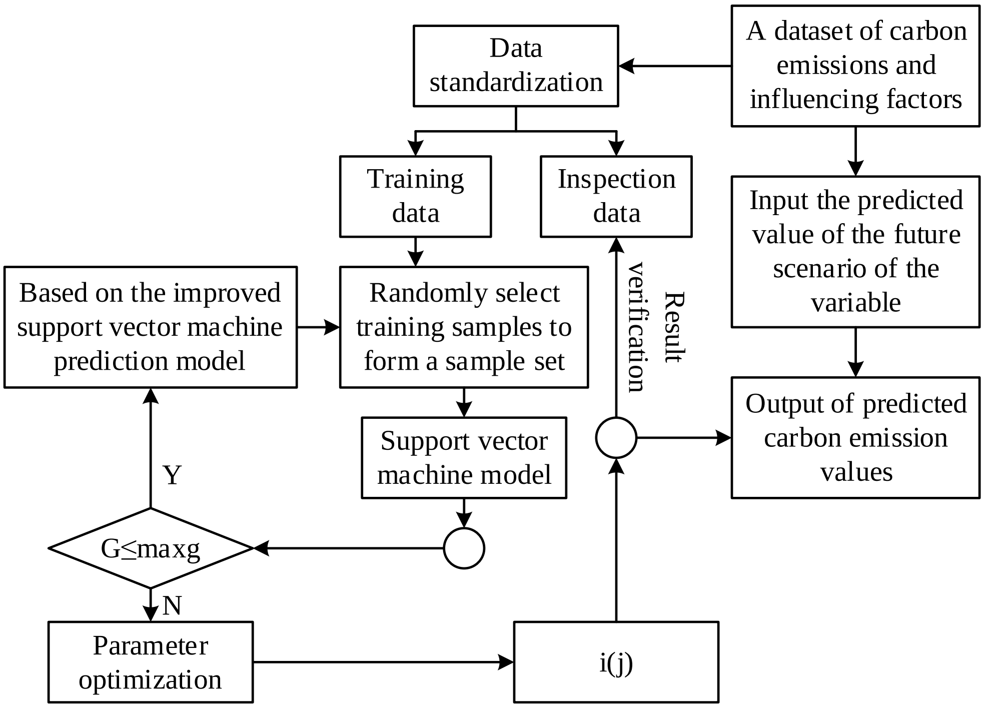


Figure 7: The structure of the improved support vector machine prediction model

4.2 Model Comparison and Analysis

The following section aims to develop a model predicting carbon emissions of buildings based on the aforementioned eight predictor variables. In order to make comparisons and select an appropriate model, three commonly used regression models such as PCR, RF, and MLP were considered.

4.2.1 Model Evaluation Metrics

The evaluation metrics are expressed as follows:

$$R^2 = 1 - \frac{\sum_{i=1}^{n} (y_i - \hat{y})^2}{\sum_{i=1}^{n} (y_i - \bar{y})^2} \tag{19}$$

$$RMSE = \sqrt{\frac{\sum_{i=1}^{n} (\hat{y}_i - y_i)^2}{n}} \tag{20}$$

$$MAE = \frac{\sum_{i=1}^{n} |\hat{y}_i - y_i|}{n} \tag{21}$$

$$NRMSE = \frac{\sqrt{\frac{\sum_{i=1}^{n}(\hat{y}_i - y_i)^2}{n}}}{y_{\max} - y_{\min}} \tag{22}$$

$$CV(RMSE) = \frac{\sqrt{\sum_{i=1}^{n}(\hat{y}_i - y_i)^2}}{n} \tag{23}$$

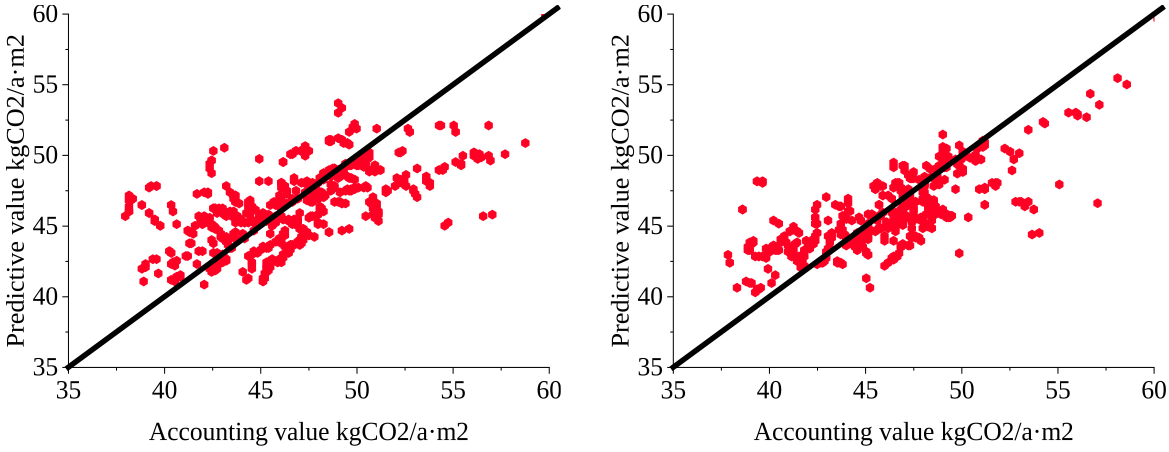
In the formula, $\hat{y}_i$ and y_i represent the predicted value and the actual value, respectively. $\bar{y}$ denotes the mean value, while $y_{\max}$ and $y_{\min}$ refer to the maximum and minimum values, respectively. n is the sample size.

4.2.2 Model Comparison Results

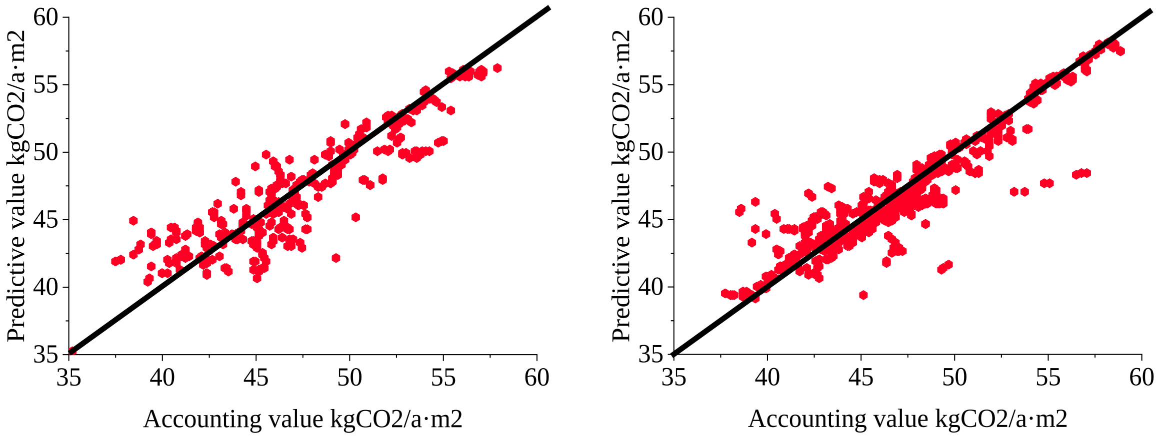
Four techniques such as PCR, RF, MLP, and IGWO-SVM have been used to build prediction models for calculating building lifecycle carbon emissions in this paper. The results of comparison of each prediction model output values against calculated values are presented in Figure 8. Figures (a) to (d) represent comparisons between the output values and calculated values of prediction models of PCR, RF, MLP, and IGWO-SVM, respectively. In order to show graphically the variation in prediction results among these models, the values of carbon emissions have been calculated and predicted through selected 30 building cases, which is illustrated in Figure 9. Both figures demonstrate the difference between the output values and calculated values of each prediction model and variations among these models. The IGWO-SVM model achieved an R^2 value of 0.811, surpassing the 0.359–0.741 ranges of other models by 9.45%–125.91%. Its RMSE, MAE, NRMSE, and CV(RMSE) results were 1.795, 1.228, 0.093, and 0.037, respectively, all lower than the comparison models. The RMSE decreased by 19.54% to 44.12%, the MAE decreased by 25.71% to 51.97%, the NRMSE decreased by 12.26% to 47.46%, and the CV(RMSE) decreased by 15.91% to 51.32%. The following conclusions can be drawn:

(1) Predictive Performance. According to evaluation criteria for the predictive model, the hierarchy of predicting building carbon emissions using different methods is IGWO-SVM > MLP > RF > PCR. The IGWO-SVM showed better predictive performance than other methods, confirming the effectiveness of this method in dealing with a small number of samples and high-dimensional data sets. MLP is placed in the second position, indicating that the neural network approach works well as a predictor if it is well-trained or has adequate learning capacity. Nevertheless, the prediction capability of the RF algorithm was found to be inferior to the other two approaches. This could be because the algorithm discretizes the continuous data while constructing the decision tree. As a result, there is some loss of data from the original dataset.

(2) Nonlinear data problems. In the four models mentioned above, PCR mainly utilizes linear regression analysis, which performs poorly in terms of prediction accuracy. On the other hand, RF, MLP, and IGWO-SVM have greater capability in dealing with nonlinear data due to their strong ability for nonlinear mapping. They can discover complicated data structures and achieve better results than PCR in terms of prediction accuracy.



(a)PCR results (b)RF results



(c)MLP results (d)IGWO-SVM results

Figure 8: Comparison of predictive values and accounting values of each model

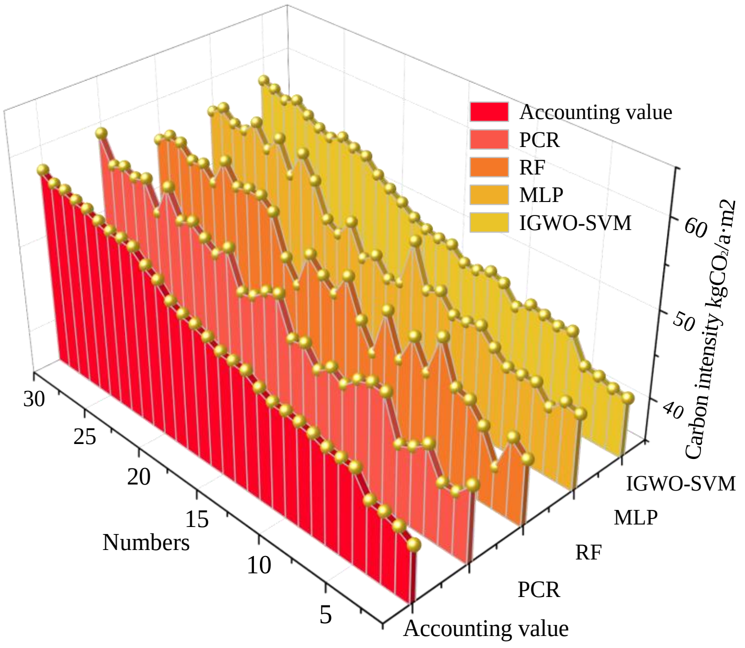


Figure 9: The comparison between the value of carbon emissions and the predicted value

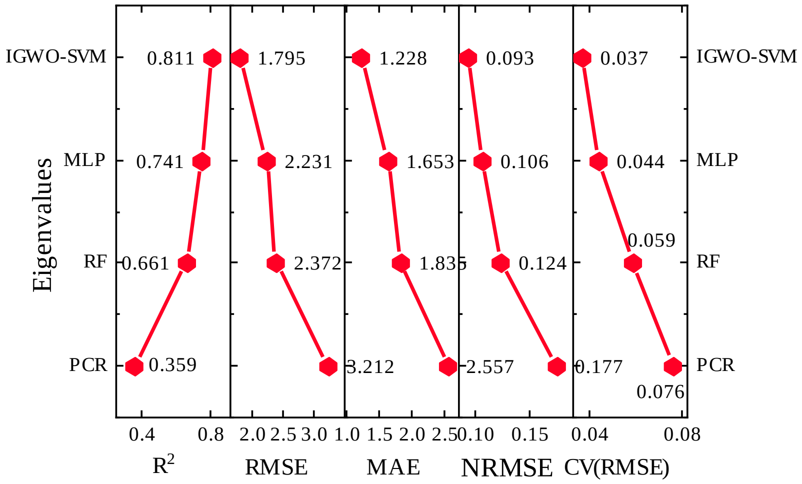


Figure 10: Evaluation indicators of each prediction model

5 Conclusion

A rational green building design may help provide a more environmentally favorable context conducive to humans' survival and production behaviors. In this paper, the research is conducted from the angle of carbon emission prediction modeling in buildings, adopting BIM technologies to aid in the acquisition of building carbon emissions data, architectural design factor selection, and model construction using intelligent models based on support vector machine algorithms combined with gray wolf algorithms. Accordingly, eight major parameters influencing the carbon emissions from buildings have been identified as follows: building shape factor, building orientation, external wall heat transfer coefficient, roof heat transfer coefficient, external window heat transfer coefficient, north facade window-to-wall ratio, west facade window-to-wall ratio, and east facade window-to-wall ratio. Out of the aforementioned parameters, the external wall heat transfer coefficient had the highest correlation with carbon emissions (-0.546), whereas the south facade window-to-wall ratio had the lowest correlation with carbon emissions (-0.045). While RMSE, MAE, NRMSE, and CV(RMSE) decreased by 19.54%–44.12%, 25.71%–51.97%, 12.26%–47.46%, and 15.91%–51.32%, respectively. This indicates superior carbon emission prediction performance of the IGWO-SVM model.

Since this model is used to predict carbon emissions from buildings, which is rather easy to implement, it makes it easy for designers to use the model for carbon emission estimations within a short period of time in the process of designing. Designers can easily make use of this model in order to determine energy consumption and carbon emissions for their designs.

Funding

This work was supported by Fujian Province Education and Scientific Research Project for Young and Middle-aged Teachers (Science and Technology Category): "Research on Multi-objective Intelligent Optimization of Concrete Floor Systems for Green Construction" (Project No. JAT251255).

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