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Comprehensive Evaluation of Carbon Emissions from Residential Buildings Based on the TOPSIS Method

Zongyang Zhang[1,*], Xinyao Lin[2], Yuqi Chen[3]

[1]College of Finance and Economics, Shanghai Lida University, Shanghai, China
[2]College of Finance and Economics, Shanghai Lida University, Wenzhou, China
[3]College of Finance and Economics, Shanghai Lida University, Taizhou, China
**Corresponding author*

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Abstract: Carbon emission reduction is a challenge and an opportunity for all countries in the world. In this paper, the Delphi method is applied to screen the indicators affecting carbon emission, and the first and second level weighting indicators are derived according to Spearman, heat map, and entropy weighting method, and the building life cycle carbon emission indicator system is established. Then, taking Jiangsu Province as an example, the TOPSIS method was used to comprehensively evaluate the carbon emission of buildings in prefecture-level cities in Jiangsu Province, and concluded that the carbon emission of Suzhou City residence is the most reasonable and ideal compared with other regions ten, and verified the reliability of the model. Finally, this paper is based on the construction of LSTM, linear regression, LGBM, decision tree, etc. on the carbon emissions of Jiangsu Province with the guessing model, after comparison, LSTM model performance is more excellent, so we chose the LSTM model for the measurement, and concluded that in 2023, the carbon emissions of Jiangsu Province are expected to be 127,902,900 tons.

1. Introduction

The "dual-carbon" approach is divided into two parts, striving to achieve carbon peaking by 2030 and carbon neutrality by 2060. The ecological environment is becoming increasingly serious, and the strategy of green environmental protection has become a consensus around the world. China has implemented a "dual-carbon" program to accelerate the pace of reducing carbon emissions and vigorously promote green and low-carbon scientific and technological innovation in order to improve the global competitiveness of industries and the economy. Low-carbon building refers to reducing fossil energy use, improving energy efficiency, and reducing carbon dioxide emissions throughout the life cycle of building materials and equipment manufacturing, construction, and building use. At present, low-carbon building has gradually become a mainstream trend in the international building community [1].

In this paper, through the study of residential buildings, according to the construction system, the use of a series of models to predict and analyze the carbon emissions of residential buildings, in order to address the problem of directionally looking for more effective ways to reduce emissions, accelerate the realization of the "dual-carbon" plan, the implementation of low-carbon buildings, to promote the country's green and low-carbon innovation, and to respond positively to our country's call for carbon neutrality.

2. Determination of an indicator system for carbon emissions related to the life cycle of buildings

2.1. Screening and identification of indicators

This paper applies the Delphi method to screen the indicators, summarizes and analyzes the feedback from experts in each round, and refines the questionnaire in each round, deciding by the mean value of the correlation of the expert's choices, and if the mean value of the results of the experts' choices in three times is more than 3, the indicator will be selected as one of the indicators in the final indicator system.

Based on the results of three rounds of expert consultation, as well as continuous modification and elimination, the indicator system for building life cycle carbon emissions as shown in Figure 1 was finalized:

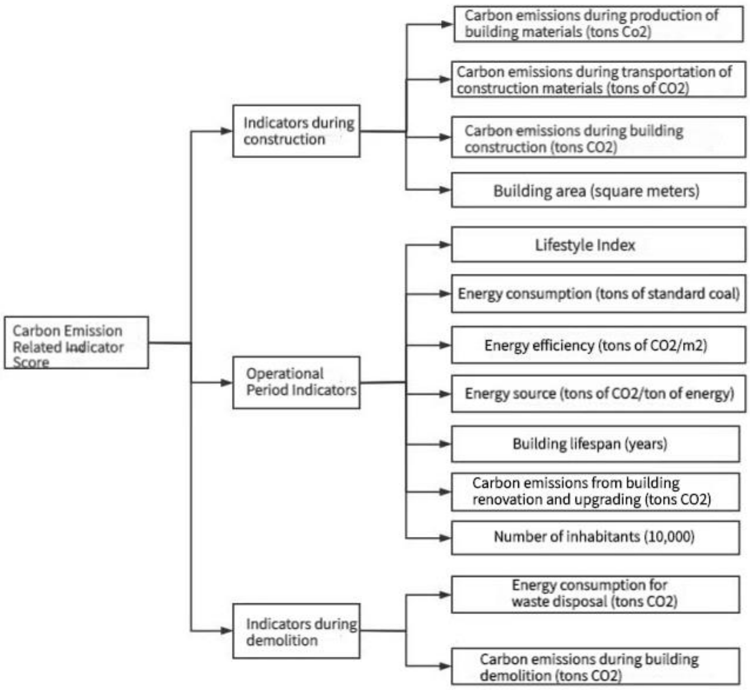

Figure 1: Indicator system for building life cycle carbon emissions.

2.2. Indicator system correlation and weighting analysis

In the building life cycle carbon emission indicators, according to the level of detail is divided into primary indicators and secondary indicators to set weights, according to the relevant literature, the importance of domestic and international regulations, we synthesize the above analysis to determine the following indicator weights: construction stage indicators (25%), operation stage indicators (70%), demolition stage indicators (5%).

(1) Data collection

In order to better analyze the following and determine the weights of the secondary indicators, this paper launched the collection of data on thirteen prefecture-level cities in Jiangsu Province. The data used in this paper are selected from the reports released by the National Bureau of Statistics, Jiangsu Provincial Bureau of Statistics, Jiangsu Provincial Prefecture and Municipal Bureau of Statistics, Jiangsu Provincial Department of Ecology and Environment, and the China Building Energy Efficiency Association, and some of the yearbook statistical data that are similar to the indicators proposed in the text or can be directly provided for the calculation of calculations, and the following items can be found as the raw data are selected. This paper targets the main source of data for the relevant part of 2021.

(2) Spearman correlation coefficient analysis:

The spearman correlation coefficient is defined as the Pearson correlation coefficient between rank variables. For a sample with a sample size of n, n raw data are converted into rank data with a correlation coefficient p:

$$p=\frac{\sum_i (x_i-\bar{x})(y_i-\bar{y})}{\sqrt{\sum_i (x_i-\bar{x})^2 \sum_i (y_i-\bar{y})^2}} \tag{1}$$

In practice, the link between the variables is irrelevant, and so it is possible to compute p, the difference between the ranks of the two variables being observed, in a simple step:

$$p=1-\frac{6\sum d_i^2}{n(n^2-1)} \tag{2}$$

Spearman's correlation coefficient, taking 13 indicators as variables, looking for the correlation of each indicator, and analyzing the degree of correlation of the indicators through the display of the color of the heat map as shown in Figure 2, which indicates that there is a certain degree of correlation of the indicators with each other, but there is no serious covariance, which further illustrates that the data that we have collected is more reasonable [2].

Figure 2: Correlation coefficient heat map.

The entropy weight method model establishment idea is as follows [3]: firstly, the weight of each index is analyzed according to the results of weight calculation, then the weight analysis matrix is obtained through the results of weight calculation, and finally the analysis is summarized.

For positive indicators:

$$x'_{ij}=\frac{X_{ij}-\min(X_{1j},X_{nj},...,X_{nj})}{\max(X_{1j},X_{nj},...,X_{nj})-\min(X_{1j},X_{nj},...,X_{nj})} \tag{3}$$

For negative indicators:

$$x'_{ij}=\frac{\max(X_{1j},X_{nj},...,X_{nj})-X_{ij}}{\max(X_{1j},X_{nj},...,X_{nj})-\min(X_{1j},X_{nj},...,X_{nj})} \tag{4}$$

In summary, according to Spearman, heat map and entropy weighting method, the first and second level weighting indicators are derived as in Table 1.

Table 1: Indicator weights

Level 1 indicators	Secondary indicators	Weights
Construction phase indicators (0.25)	Carbon emissions from the production of building materials (tons of CO2)	0.33391
	Carbon emissions from transportation of construction materials (tons CO2)	0.19679
	Carbon emissions from building construction (tons of C02)	0.27605
	Floor area (square meters)	0.19325
Operational phase indicators (0.70)	Energy consumption (tons of standard coal)	0.19901
	Energy use efficiency (tons CO2/m2)	0.15328
	Energy sources (tons of CO2/ton of energy)	0.08529
	Number of inhabitants (10,000)	0.18318
	Lifestyle index	0.24107
	Useful life of building (years)	0.06366
	Carbon emissions from building renovation and upgrading (tons CO2)	0.0745
Indicators for the dismantling phase (0.05)	Carbon emissions from building demolition (tons CO2)	0.5744
	Energy consumption for waste treatment (tons of CO2)	0.4256

In the construction phase, the maximum weight of the indicator is 33.391% of the floor area, and the minimum value is 19.325% of the carbon emission during building construction; in the operation phase, the maximum weight of the indicator is 24.107% of the lifestyle index, and the minimum value is 6.366% of the building's service life; and in the dismantling phase, the maximum weight of the indicator is 57.44% of the energy consumption of waste disposal, and the minimum value is 42.56% of the carbon emission during building dismantling. In the demolition stage, the maximum value of the indicator is 57.44% of energy consumption for waste disposal, and the minimum value is 42.56% of carbon emission during the building demolition.

3. Comprehensive Evaluation of Carbon Emission from Residential Buildings in Prefectural Cities of Jiangsu Province Based on TOPSOS Method

The TOPSIS method is a commonly used comprehensive evaluation method within a group, which can make full use of the information of the original data, and its results can accurately reflect the gap between the evaluation programs. The basic process is based on the normalized original data matrix, using the cosine method to find out the optimal and the worst options in a limited number of programs, and then calculate the distance between each evaluation object and the optimal and worst options, to obtain the relative proximity of each evaluation object to the optimal program as a basis for evaluating the advantages and disadvantages. The method has no strict restrictions on data distribution and sample content, and the data calculation is simple and easy to implement [4].

Step 1: Prepare the data, and carry out the same trend processing of the original data, and the quantization of positive and negative indicators.

Construct a matrix X_j of n rows and m columns, where X denotes the value of the jth indicator for the ith object.

Step 2: Construct a standardization matrix.

$$Z_{ij} = \frac{X_{ij}}{\sqrt{\sum_{k=1}^{n}(X_{ij})^2}} \tag{5}$$

Step 3: Calculate the gap between each evaluation metric and the optimal and worst vectors.

$$D_{\mathrm{i}}^{+} = \sqrt{\sum_{j=1}^{m} w_j \left(Z_j^{+} - z_{ij}\right)^2}, D_i^{-} = \sqrt{\sum_{j=1}^{m} w_j \left(Z_j^{-} - z_{ij}\right)^2} \tag{6}$$

Where w_j is the weight (importance) of the jth attribute.

Step 4: Measure the proximity of the evaluation object to the optimal program.

$$C_{\mathrm{i}} = \frac{D_i^{-}}{D_i^{+} + D_i^{-}} \tag{7}$$

The larger the C_i-value, the better the evaluator.

Table 2 below shows the results of the TOPSIS evaluation method calculations.

Table 2: TOPSIS evaluation results

Index value	Positive ideal solution distance (D+)	Negative ideal solution distance (D-)	Composite score index	Arrange in order
Nanjing	0.69809749	0.61708646	0.46920163	9
Wuxi	0.52755212	0.57324389	0.52075397	7
Xuzhou	0.63470897	0.46258529	0.42156905	13
Changzhou	0.49179758	0.58205853	0.54202656	3
Suzhou	0.50590885	0.74990562	0.59714682	1
Nantong	0.6063662	0.49740198	0.4506399	12
Lianyungang	0.62927731	0.62339374	0.49765159	8
Huaian	0.67342954	0.56485195	0.45615795	11
Yancheng	0.59422483	0.51193571	0.46280417	10
Yangzhou	0.56325176	0.61945265	0.52375948	5
Zhenjiang	0.52120704	0.67771033	0.56526859	2
Taizhou	0.55727157	0.6164834	0.52522325	4
Suqian	0.63979439	0.69790972	0.52172204	6

D+ and D- values represent the distance (Euclidean distance) between the evaluation object and the optimal or worst solution (i.e., A+ or A-), respectively. The practical significance of these two values is that the larger the value of the evaluation object, the greater the distance between the evaluation object and the optimal or worst solution, the greater the value indicates the further the distance is, the greater the value of D+ of the object of study indicates the further the distance from the optimal solution, while the greater the value of D-, the further the distance from the worst solution is. The most understood research object is the D+ value is smaller at the same time D-value is larger.

Comprehensive degree score C value, C = (D-) / (D + + D-), the formula, the numerator is the D-value, the denominator is the sum of D + and D-; D- value is relatively larger, it means that the research object is farther away from the worst solution, then the research object is better; the larger the value of C means that the research object is better.

4. Carbon Emission Prediction Model for the Whole Building Process in Jiangsu Province

4.1. Data sample preprocessing

According to the data released by the National Bureau of Statistics, we can get the historical data of carbon emission of the whole process of construction in Jiangsu Province as follows Table 3.

Table 3: Historical data on whole-process carbon emissions from buildings in Jiangsu Province

Year	Building carbon emissions (10,000 tons)
2006	7420.41974
2007	7710.150069
2008	8375.931797
2009	8549.023878
2010	10098.11177
2011	9878.986544
2012	11168.62072
2013	12223.45499
2014	11537.3525
2015	12124.62064
2016	11894.46429
2017	11942.99249
2018	12067.16588
2019	12150.42279
2020	12160.96008
2021	12535.85919
2022	12894.46429

4.2. Define the predictive power of the indicator for the model

Predict the entire test set and compare the predicted data with the actual data. In order to evaluate the performance and prediction of the model, the root mean square error average absolute error and the average absolute percentage error, R^2, were chosen as the evaluation metrics of the model based on the predicted and actual observations.

Their formulas are shown below, respectively:

$$RMSE = \sqrt{\frac{1}{N}\sum_{i=1}^{N}(y_i' - y_i)^2} \tag{8}$$

$$MAE = \frac{1}{N}\sum_{i=1}^{N}\left|y_i' - y_i\right| \tag{9}$$

$$MAPE = \frac{1}{N}\sum_{i=1}^{N}\left|\frac{y_i' - y_i}{y_i}\right| \tag{10}$$

$$R^2 = \frac{SSE}{SST} = 1 - \frac{SSE}{SST} = 1 - \frac{\sum\left(Y_i - \hat{Y}\right)^2}{\sum\left(Y_i - \bar{Y}\right)^2} \tag{11}$$

Where y' is the predicted value, y is the straight real value and N is the number of samples in the test set. When the value of RMSE, MAE and MAPE is smaller, it means that the error between the predicted value and the actual observed value is smaller, and furthermore, it means that the performance of the used prediction model is better, and R^2 is on the contrary, the closer to 1, it means that the performance of the used prediction model is better.

4.3. Carbon emission model

In this paper, LSTM, linear regression, LGBM, decision tree [5] and other prediction models of carbon emissions in Jiangsu Province are constructed, and the results are shown in Table 4. Among them, the curves predicted by LSTM and linear regression are shown in Figures 3 and 4.

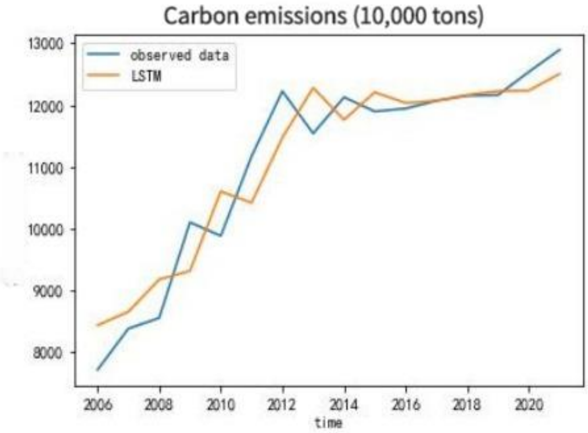

Figure 3: Correlation coefficient heat map.

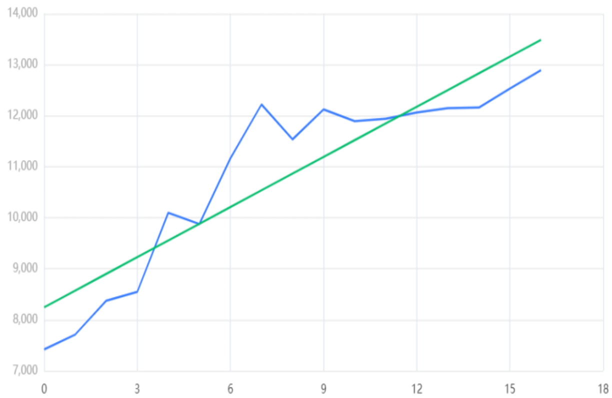

Figure 4: Correlation coefficient heat map.

Table 4: Model Prediction Effect

	Training set MAPE	Test set MAPE	MAE	R^2
LSTM	0.115	0.125	1396.3444619594102	0.9652156429393133
Linear regression	0.041	0.071	709.092663991014	0.7298678497457729
Decision tree	0.150	0.232	823.791898697445	0.6391382207876317
LGBM	0.115	0.125	1396.3444619594102	0.9652156429393133
XGBOOST	0.150	0.232	823.7932333530898	0.639136824466869

In summary, based on a variety of regression methods surface here LSTM model analysis error is the smallest, the most accurate, for the next year to predict that the carbon emissions from residential buildings in Jiangsu Province in 2023 is 127, 902, 900 tons.

5. Conclusions

In this paper, the initial indicator system was established through reference literature and research and after three rounds of consultation with nine experts and professors engaged in ecology or architecture, the indicators were screened out and three types of primary indicators and thirteen secondary indicators of the building life cycle emission indicator system were formed for the comprehensive evaluation of the life cycle emission of the building. Then the weights of the first and second level indicators were divided, in which the first level indicators were combined with the domestic and foreign literature, the second level indicator system was perfected by adopting the entropy weight method and Delphi method, and the weights of the indicator system were collated and obtained, and the results of the study showed that the weights of the operational and construction phases of the 1st level indicator system were 0.7 and 0.25 respectively, and the weights of the dismantling phase were relatively small, and the weights of the 2nd level indicators were relatively small, and the weights of the dismantling phase were relatively small, and the weights of the 2nd level indicators were relatively small. Modeling approach to screen the indicators with high relevance.

Based on the indicator system established above, this paper adopts the TOPSIS method to comprehensively evaluate the carbon emissions of buildings in prefecture-level cities in Jiangsu Province, which results in the highest ranking of carbon in residential buildings in Suzhou and the last in Xuzhou. Therefore, the carbon emissions of Suzhou's residential compared to other regions ten the most reasonable and ideal. Finally, the LSTM model was constructed to predict the whole process of carbon emissions from buildings in Jiangsu Province, resulting in an estimated carbon emission of 127.9029 million tons in Jiangsu Province in 2023.

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