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Research on Carbon Emission Prediction based on Particle Swarm Optimization

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Abstract

The construction of China's ecological civilization has entered a critical period in which carbon reduction is the key strategic direction, pollution reduction and carbon reduction synergies are promoted, the overall green transformation of economic and social development is promoted, and the quality of the ecological environment is improved from quantitative to qualitative. But not only China, but also the whole world has not paid much attention to it. This article analyzes the data from the two main lines, combines the particle swarm optimization algorithm, and determines the actual consumption through various sub-projects in the construction industry, estimate and analyze carbon emissions in the next five years.

Keywords

PSO; Carbon Emissions; Construction Industry; Forecast.

1. Introduction

With the continuous improvement of the level of social industry and the increasing consumption of various energy sources, carbon emissions have now become a crucial issue. Carbon emissions are also "carbon dioxide emissions", and the most important greenhouse gas is carbon dioxide. Climate change [1] has seriously deteriorated the living environment of mankind and is considered to be one of the most significant challenges [2] facing mankind in the future. According to relevant United Nations reports, global greenhouse gas emissions caused by human life and production activities have maintained a growth trend for three consecutive years. At the same time, more than 4.7 million hectares of forests disappear globally every year, and the global annual runoff from glaciers will peak at the end of this century at the latest. These two superimposed effects will further aggravate the global average temperature rise. In the life closely related to us, the construction industry is the basic project of people's lives. By understanding the specific consumption of the construction industry, we can obtain the specific forecast value of future carbon emissions.

1.1. The Main Fitting Model

Usually, we will use the simplest least squares fitting to process and fit the data, but it is easy to fall into the local optimum during the fitting process, so here we use the particle swarm optimization algorithm. Particle swarm optimization [3] algorithm is an evolutionary computing technology. Originated from the study of bird predation behavior. [4] The basic idea of particle swarm optimization algorithm is to find the optimal solution through collaboration and information sharing between individuals in the group. The advantage of PSO is that it is simple and easy to implement and does not have many parameter adjustments. It has been widely used in function optimization, neural network training, fuzzy system control and other genetic algorithm application fields The core part of the update speed and position formula:

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$$V_{id} = wV_{id} + C_1 \text{ random } (0,1)(p_{id} - X_{id}) + C_2 \text{ random}(0,1)\left(P_{gd} - X_{id}\right) \tag{1}$$

$$X_{id} = X_{id} + V_{id} \tag{2}$$

Among them, w is the inertia factor, C1 and C2 are the acceleration constants, generally take $C_1 = C_2 \in [0,4]$, random (0,1) represents the random number in the interval [0,1], and p_{id} represents the i-th the d-th dimension of the individual extreme value of each variable, P_{gd} represents the d-th dimension of the global optimal solution. For the final termination condition, there are two termination conditions to choose from, one is the maximum algebra: Tmax; the other is that the deviation between two adjacent generations stops within a set range, and the first one is selected here.

2. Collection and Arrangement of Relevant Data

2.1. Historical Building Area Data

By collecting the building area data of the country in the past ten years, we can analyze that in the past ten years, the building area of the country has steadily increased, and the building area has been steadily increased within a certain range. Based on this data, the building area of the next few years will be calculated. In order to determine the future housing change trends and some more accurate numerical values, a series of subsequent related consumption situations can be calculated, and certain data support can be provided for the related carbon emission prediction of the construction industry.

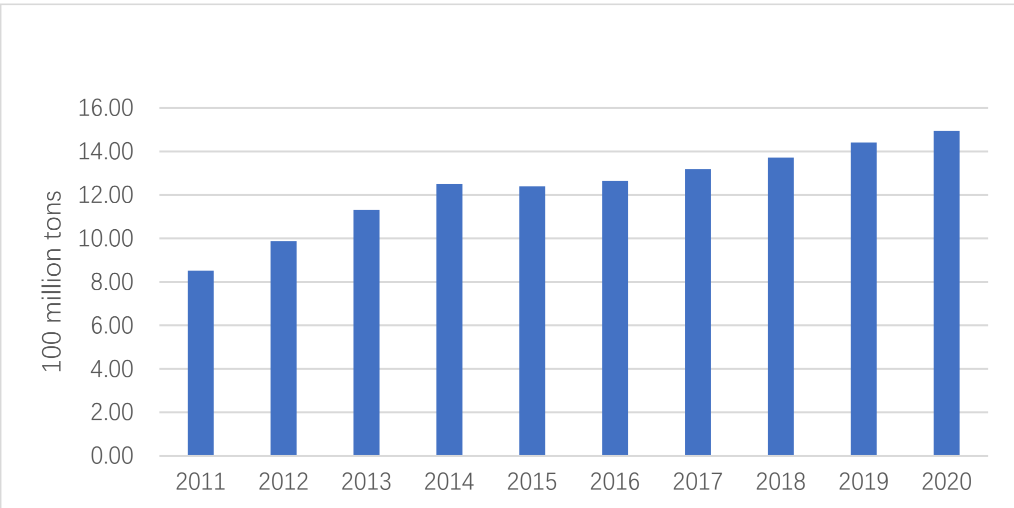

Fig 1. Historic building area (Years)

2.2. The Least Squares Method Predicts the Future Building Area of Houses

First use the following correlation coefficient to determine whether there is a linear relationship:

$$r(X,Y) = \frac{\operatorname{Cov}(X,Y)}{\sqrt{\operatorname{Var}[X]\operatorname{Var}[Y]}} \tag{3}$$

The correlation coefficient is calculated by the above formula:

$$\mathrm{r} = 0.9595$$

It shows that X and Y have a strong positive correlation, and the relationship between the two can be clearly reflected from the figure. Therefore, using the data in the previous section, the least square method is used to obtain the construction area of the construction industry. The linear regression equation is:

$$R^2 = 1 - \frac{\sum_{i=1}^{n} (y_i - \hat{y}_i)^2}{\sum_{i=1}^{n} (y_i - \bar{y}_i)^2} \tag{4}$$

The degree of fit is obtained by formula (5):

$$R^2 = 0.92063 \tag{5}$$

Goodness of fit refers to how well the regression line fits the observations. The statistic that measures the goodness of fit is the coefficient of determination (also known as the coefficient of determination) R^2. The maximum value of R^2 is 1. The closer the value of R^2 is to 1, the better the fit of the regression line to the observed value; on the contrary, the smaller the value of R^2, the worse the fit of the regression line to the observed value. In this example, the value of (5) is relatively close to 1, which means that the collected examples can be fitted with linearity to find the future trend of relevant changes:

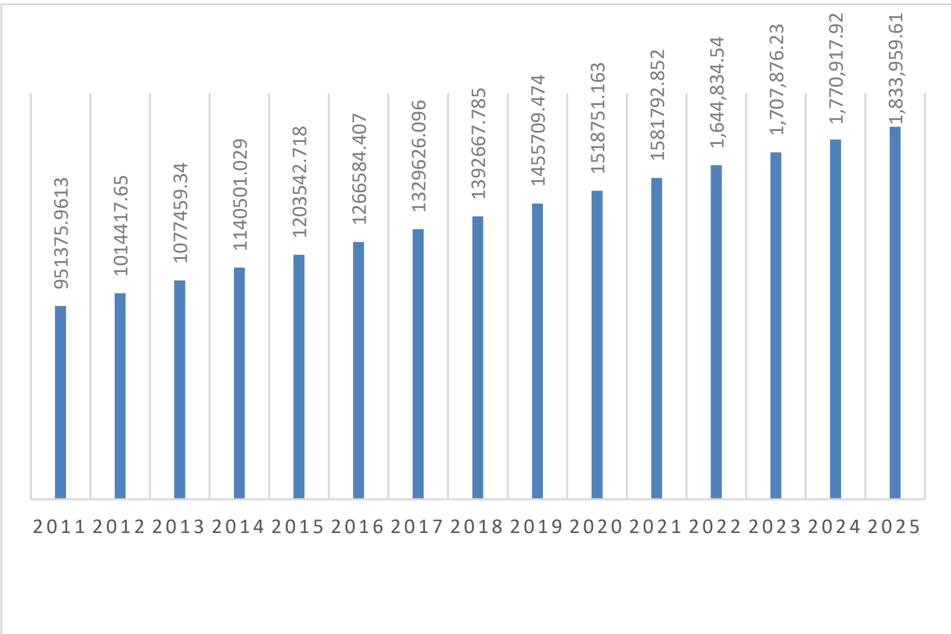

Fig 2. Future construction area forecast map (ten thousand square meters)

From the above figure, we can see that the construction area in the future will show a relatively high upward trend in a certain period of time. It will increase from 1,581,928,520 square meters in 2021 to 1,839,959,100 square meters in 2025, indicating that China's construction industry is constantly increasing. More vigorous development means that more materials and energy will be invested in it, and it also means that the value of carbon emissions will further increase, which greatly illustrates the need for us to study carbon emission models and reduce carbon emissions.

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3. Estimate the Future Carbon Emissions based on the Carbon Emissions Per Unit Area of the Building Area

3.1. Basic Carbon Emission Forecast

First, we first study specific carbon emission building examples [5], hoping to find specific carbon emission data. The total CO2 emissions from the construction of the four typical building cases are as follows:

Table 1. The total CO2 emissions from the construction of the four typical building cases

Basic situation	Case 1	Case 2	Case 3	Case 4
Place	Baotou City, Inner Mongolia	Wuxi City, Jiangsu Province	Jiyuan City, Henan Province	Baoding, Hebei
Construction time	2016	2017	2019	2018
Building Type	Commercial Building	School building	Civil building	Government building
Construction type	RC	RC	RC	RC
floor	5	3	15	8
high	23.80	14.20	61.30	34.00
Construction area	110000.00	16000.00	30000.00	43000.00
Unit CO2 emissions	11.50	11.60	11.30	12.00

The results show that although the building type in Table 1, building area and location are different, the CO2 emissions per unit area (U) are very close:

$$\mathrm{U} = 11.55\mathrm{kgCO2/m2}$$

Use the following formula to predict future carbon emissions:

$$T\mathrm{CO}_2\ (1) = \mathrm{Sa} \times \mathrm{U} \times T \tag{6}$$

Among them, TCO2 represents the total consumption of the year, and Sa represents the construction area of the year. Since the actual situation varies from year to year, set T as the annual adjustment coefficient and convert it according to the average process growth rate.

3.2. Yearly Adjustment Factor

If we get the future carbon emission forecast based only on the building area multiplied by the carbon emission per unit area, we will ignore the important factor of technological progress. Therefore, we set T as the annual adjustment coefficient, based on the past 2016-2020 The specific consumption of carbon emissions is compared to the carbon emissions obtained by multiplying the predicted area by the emissions per unit area in the above figure, and we can get the T scale coefficients for the past five years as follows:

$$T\ = 0.9, 0.75, 0.8, 0.85, 0.95 \tag{7}$$

Bring the value of (7) into (6), we can get:

Table 2. The results (1)

Year	2021	2022	2023	2024	2025
carbon emissions1 (100 million tons)	21.1	21.5	21.7	22.4	24.2

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4. Estimating Future Carbon Emissions based on Itemized Consumption of Carbon Emissions from Construction Projects

4.1. Basic Overview of Energy Consumption in the Construction Industry

First of all, from the perspective of materials used in the construction industry, in the main energy-consuming building materials sub-industry, the cement industry is the largest energy-consuming unit. Energy consumption accounts for about 57.6% of the total energy consumption of the building materials industry, with a total energy consumption of 189 million tons. Standard coal; other industries that consume more energy include sintered bricks and lime, which account for 9.89% and 9.65% of energy consumption in the building materials industry, respectively. However, sintered bricks are constantly using new materials, and the unit consumption of their use is not clear. Secondly, the carbon emissions in mechanical construction are also relatively large.

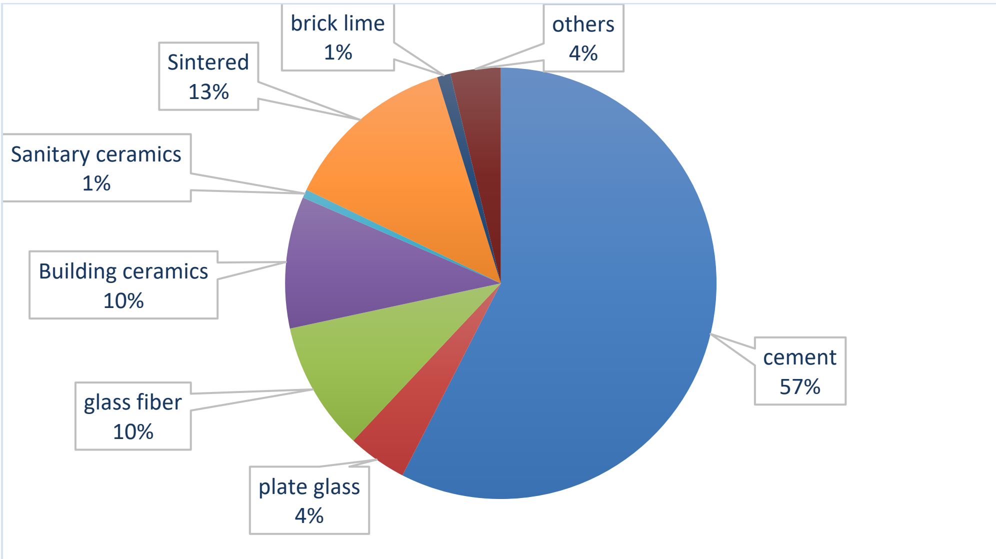

Fig 3. The proportion of energy consumption in the construction industry

4.2. Direct Construction Material Consumption and Carbon Emission Forecast

4.2.1. E_i Consumption of Direct Materials

During the use of building materials, there are nothing more than basic carbon emissions, carbon emissions from natural gas use, and carbon emissions from diesel use. The remaining emissions account for a small number. Therefore, we may wish to use these three as the main factors and calculate them based on the specific consumption in 2020. Corresponding proportions, the basic carbon emission of cement is $596.7 \mathrm{kgCO_2}/t$, the consumption of diesel and natural gas is 0; the basic carbon emission of lime is $85.14 \mathrm{kgCO_2}/t$, and the consumption of natural gas is$13.15 \mathrm{kgCO_2}/t$, Diesel consumption is $1.436 \mathrm{kgCO_2}/t$.

4.2.2. Cement Consumption and Carbon Emission Forecast

The cement consumption per square meter of building standard area is $160 \mathrm{Kg/m^2}$. It may be better to predict cement consumption through (4) and (8):

$$C_1 = \mathrm{Sa} \times P \tag{8}$$

In the formula, C1 represents the total consumption of cement, Sa represents the building area of the house, and P represents the amount of cement required per unit building area. After

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calculation, if development is carried out according to the current trend, cement consumption will be more than 2.5 billion tons in 2021 to more than 2.9 billion tons in 2025.

$$\mathrm{CO_2}c = \sum_{1}^{3} (E_i \times C_1) \tag{9}$$

Among them, $\mathrm{CO_2}c$ represents the total carbon emission of cement, and $E_i$represents the basic carbon emission factor, the carbon emission factor of natural gas consumption, and the carbon emission factor of diesel consumption. Therefore, the corresponding cement future carbon emission forecast data can be calculated by formula (9):

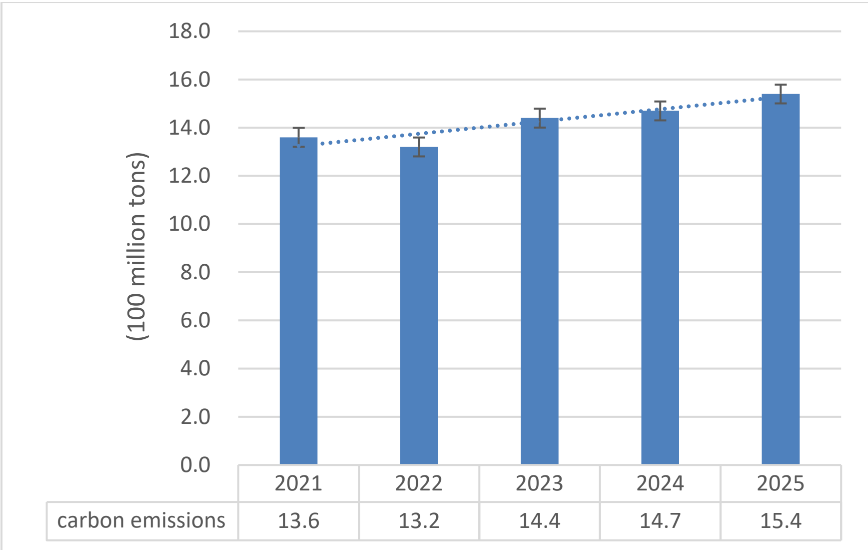

Fig 4. Cement future expected carbon emissions (Year)

4.2.3. Lime Consumption and Carbon Emission Forecast

In the same way, the lime consumption per square meter of standard building area is 13.314Kg/m^2. We use equation (4) to predict the area of the house and use equation (10) to predict lime consumption:

$$C_2 = \mathrm{Sa} \times P \tag{10}$$

In the formula, C_2 represents the total consumption of lime, Sa represents the building area of the house, and P represents the amount of lime required per unit building area According to calculations, if the development is carried out according to the current trend, the lime consumption will be more than 33 billion tons in 2021 to more than 39 billion tons in 2025.

$$\mathrm{CO_2}s = \sum_{1}^{3} (E_i \times C_2) \tag{11}$$

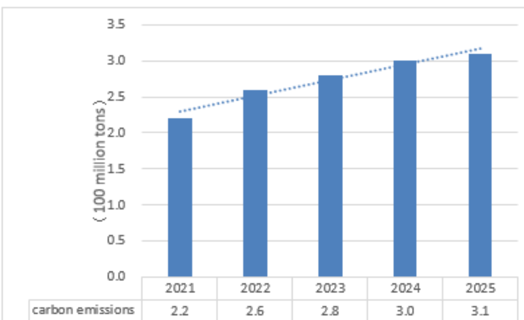

Fig 5. Lime future expected carbon emissions (Year)

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Among them, CO_2s represents the total carbon emission of cement, and $E_i$represents the basic carbon emission factor, the carbon emission factor of natural gas consumption, and the carbon emission factor of diesel consumption. Therefore, the corresponding cement future carbon emission forecast data can be calculated by formula (11):

4.3. Energy-based Construction Material Consumption and Carbon Emission Forecast

4.3.1. The Concept of Mechanical Consumption Estimation

In the process of specific calculations, because the construction process of a construction project consists of hundreds or thousands of unit processes, collecting all necessary site-specific data will consume a lot of time and cost. Therefore, many researchers have studied building construction from a macro perspective. For the CO2 emissions in the process, the research is based on national statistics and does not rely on on-site data surveys. However, this macro-scale method usually cannot obtain the detailed source of CO2 emissions, which will cause data distortion and inaccuracy. Therefore, the emission factor model is used to measure the emissions of machinery consumption.

4.3.2. Introduction to Mechanical Consumption Estimation Model

The operation of construction machinery is the most important source of carbon emissions for field operations. This paper studies the CO2 emissions of large construction machinery. The calculation formula is as follows:

$$CE_i = \sum_{i=1}^{3} M_j \times EF_j \tag{12}$$

Where: CE_i is the CO_2 emissions of 1 shift of i machinery (ie the carbon emission factor consumed by construction machinery, $kgCO_2e$ /shift); M_j is the energy consumption of type j for 1 shift of i machinery; EF_j is j Emission factor of type energy. There are 3 types of energy sources commonly used, namely diesel, gasoline and electricity.

According to the calculation of the "China Greenhouse Gas Inventory Study" issued by the Climate Change Department of the National Development and Reform Commission in 2005, the emission factors of China's diesel and gasoline can be obtained as 3. 1451 $kgCO_2e$ /kg and 3. 0425 $kgCO_2e$ /kg, and the calculated electricity emission coefficient is 0. 6101 $kgCO_2e$ /kWh.

The total amount of emissions from all machinery in the entire project during the construction process is calculated as follows:

$$CE_{\mathrm{T}} = \sum_{i=1}^{m} CE_i \times MC_i \tag{13}$$

In this formula: CET is the CO2 emissions during the construction process (kgCO2); CE_i is the carbon emission factor of i machinery (kgCO_2 e/unit); $MC_i$is the consumption of i machinery (unit); m is the construction process the number of machinery used in.

4.3.3. Practical Examples

Let us take the rail-mounted diesel piling machine as an example. Its energy type is diesel and electric. The diesel energy consumption is 56.9kg/md, and the electricity consumption is 171.00kWh/md. After calculation, we can get: rail-mounted diesel piling The CO2 emission of the engine is 283.28kgCO2 /md. According to the above calculation process, the results of various mechanical carbon emissions (kgCO_2/md) are finally obtained:

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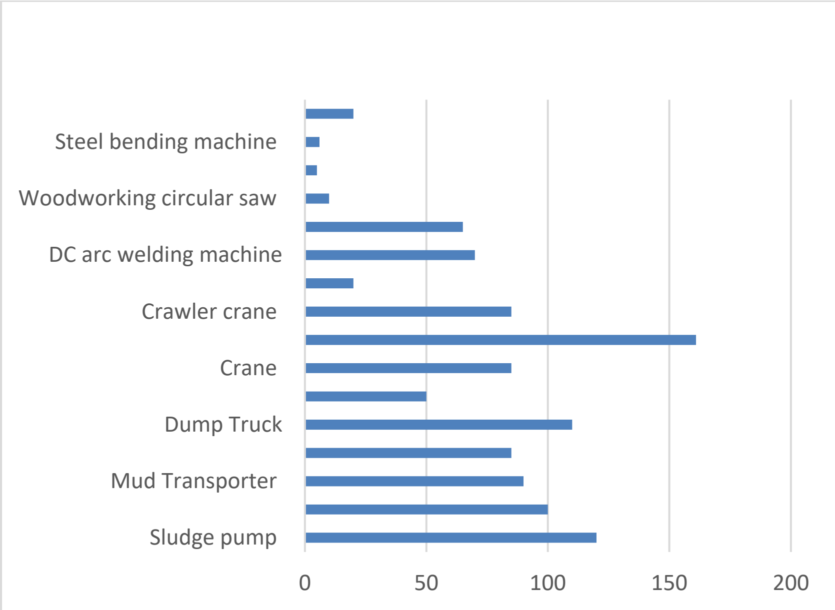

Fig 6. Specific construction machinery consumption(partial)

Through formulas (12) (13) we can find:

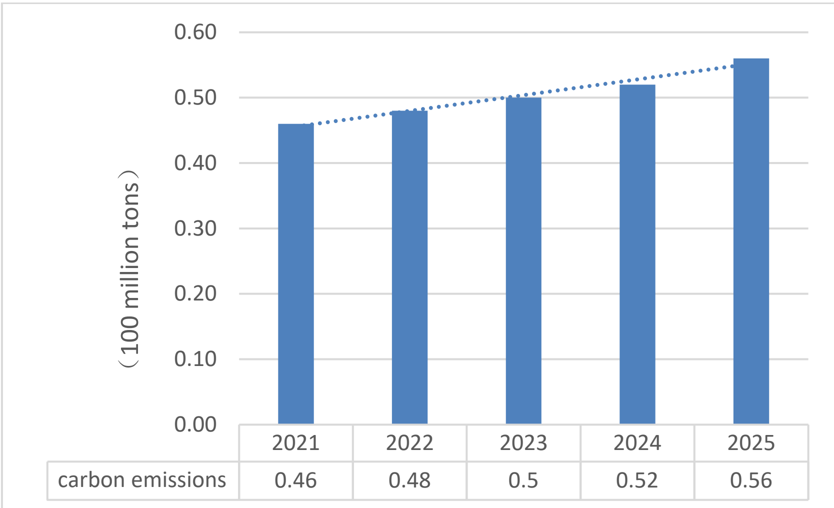

Fig 7. The future expected carbon emissions of steel bars (Year)

4.3.4. Total Carbon Emission Model

According to formula (8)(9)(10)(11)(12)(13), the corresponding carbon emission model is comprehensively put forward:

$$TCO_2(2) = \frac{CO_2c + CO_2s + CE_T}{Kt} * T = \sum_{j=1}^{2}\sum_{i=1}^{3}\left(\frac{(E_i \times C_j)}{Kj}\right) * T + \frac{CE_T}{K3} \tag{14}$$

In the formula, Ei represents the CO2 generated per kilogram of material, Ci represents the specific consumption, Ki represents its proportion in building emissions, Kt represents the combined proportion of the three, and the corresponding proportion can be obtained according to the Fig 3.

After calculation by formula (14), we can get:

Table 3. The results (2)

Year	2021	2022	2023	2024	2025
carbon emissions2 (100 million tons)	19.2	20.0	20.6	21.3	22.0

5. Estimation of Carbon Emissions from the Construction Industry in the Future

We might as well use the particle swarm optimization algorithm to fit the future carbon emission data obtained in the two ways in order to obtain a more accurate carbon emission forecast.

First, we set the maximum number of iterations Tmax=500, the number of independent variables of the objective function, the maximum speed of the particle is 10, and the position information is the entire search space. We randomly initialize the speed and position in the speed range and search space, and set the particle swarm the scale is 50, each particle randomly initializes a flying speed, the interval range of the fitting parameters is set to [-5,5], and the learning factor is C1=C2=2. On this basis, we use MATLAB and Python to perform the fitting solution.

The number of iterations is tested through the MATLAB program, and the optimal number of historical iterations is shown in the Figure below:

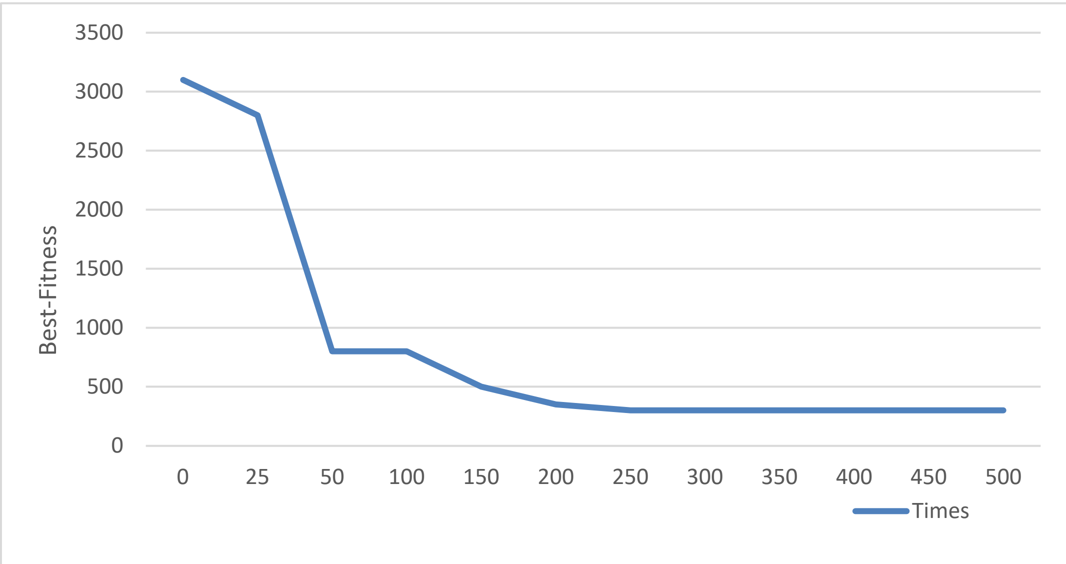

Fig 8. Optimal fitness change

It can be seen from the Fig 8 that about 200 iterations start to stabilize, and the following iterations will start to find the historical optimal particle swarm. Here, the parameter setting of the inertia factor in the particle swarm algorithm is particularly important in this example, in order to better balance the global search of the algorithm. Ability and local search ability, Shi. Y proposed linearly decreasing inertia weight (LDIW), namely:

$$w(k) = w_{\text{end}} + (w_{\text{start}} - w_{\text{end}}) * \frac{(T_{max} - k)}{T_{max}} \tag{15}$$

Where Wstart is the initial inertia weight, Wend is the inertia weight when the iteration reaches the maximum number of times; k is the current iteration number, and Tmax is the maximum iteration number. Generally speaking, when Wstart = 0.9 and Wend = 0.4, the algorithm has the best performance. As the iteration progresses, the inertia weight decreases from 0.9 to 0.4. The larger inertia weight at the beginning of the iteration enables the algorithm to maintain a strong global search. ability. The smaller inertia weight at the later stage of the iteration is conducive to the algorithm for more accurate local search.

Through (1)(2)(15), we can get the fitting curve through the Python algorithm. We import the predicted value, Table 2 and predicted value Table 3 into MATLAB and display them in the following Fig 9:

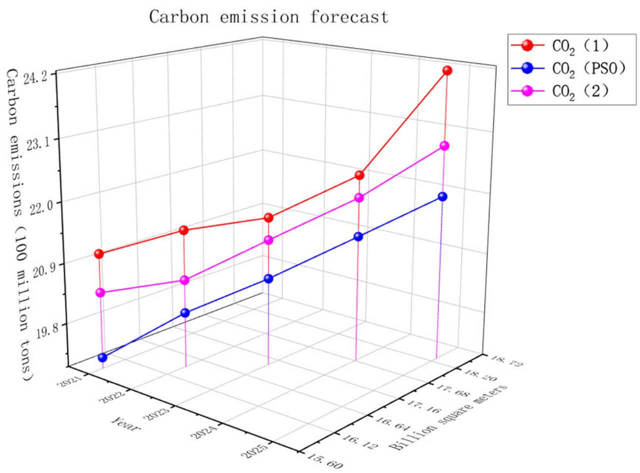

Fig 9. Carbon emission forecast curve

6. Conclusion

It is not difficult to see from the Figure that the difference between the first and third curves is too large. Generally speaking, taking any one of them as the prediction result will increase the inaccuracy of the final expected information, so we might as well use the PSO curve, which is not only It only has a comprehensive effect, and to a certain extent, it avoids the shortcomings of the local optimization of the least squares method. At the same time, its predicted value ranges from 1.92 billion tons to 2.20 billion tons, which is more in line with the actual carbon emission curve. Therefore, we have determined that the predicted value obtained by the PSO model is more reliable.

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