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Summary

It has become more important for governments all over the globe to achieve carbon neutrality and maximum carbon emissions as a result of the greenhouse effect and rising carbon dioxide emissions. However, to satisfy the demands of the market, the industry has increased output to meet the growing living standards and rapid technical advancements. This has resulted in the unintended worsening of the climate crisis. Therefore, implementing an effective measure is crucial for governments and industry to achieve a better environment.

Presently, there exists an electronic equipment manufacturing facility that is required to decrease its carbon dioxide emissions. The proposed strategies to attain the aim include: decreasing the site size, minimizing labor, providing comfortable and cost-effective working conditions, and reducing and recycling packaging materials. However, each metric will result in varying amounts of carbon dioxide emissions, with varied correlations between these measurements. Thus, in our model, we employ **life cycle evaluations** and a **multivariate model** to estimate the decrease in carbon dioxide emissions resulting from various strategies and determine the specific link. In conclusion, the reduction of the site size, labor, working conditions, and packing materials has resulted in a reduction of the yearly carbon emissions. These eco-friendly actions brought in a reduction in carbon emissions of **22.57%, 33.40%, 39.14%, 4.89%** respectively. Through the implementation of this holistic plan, resource efficiency, ecological sustainability, and environmental responsibility are emphasized. The use of these solutions offers a complete and efficient strategy for controlling

Moreover, owing to the different effects of distinct approaches, the effectiveness of measures should be evaluated. Therefore, the **TOPSIS analysis** is utilized in the model to assess the measures. By considering the two factors-reduction of carbon dioxide emissions and reduction of coal-that impact the effectiveness of measures, we ranked the four methods and found the best and worst options. **Minimizing the workload** is undeniably the most effective approach to decrease carbon dioxide emissions. Conversely, the efforts aimed at **minimizing packaging materials and recycling** them have the lowest rating and are the least effective.

Following the analysis of two separate elements and the previous TOPSIS evaluation, we suggest a new approach to mitigate carbon dioxide emissions: **Bicycle Commuting**. It will decrease about $30t$ of carbon dioxide emissions and 1273 units of coal use. Upon reevaluating the new measure in relation to the other four measures, we have determined that the strategy of bicycle commuting consistently ranks in the **top position**.

The passage may be employed to educate the industry and companies on using the most efficient methods to manage and decrease carbon dioxide emissions, so assisting governments in achieving carbon neutrality and reaching the peak of carbon emissions.

Keywords: life Cycle Assessment; TOPSIS Analysis; Carbon Dioxide Emission; multivariate model

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1 Introduction

1.1 Background

Rising carbon dioxide emissions and the greenhouse effect have pushed governments worldwide to attain carbon neutrality and maximum carbon emissions. However, with rising living standards and rapid technological advances, industry has expanded production to meet market demand, inadvertently exacerbating the climate problem.

Effective emission reduction measures must be implemented quickly across all industries. This article investigates some measures to reduce CO_2 in a specific electronic device plant. The measures include reduction of site area, reduction of labor, provision of comfortable and cost-efficient working conditions, and reduction and recycling of packaging materials.

Reduction quantities of carbon dioxide for each measure are the focus of this article, analyzed based on numerous factors. Additionally, the article recommends new methods (yet to be identified) to assist factories in adopting the most effective emission reduction techniques.

1.2 Problem Restatement

- **Determine four quantitative functions** that substitute for the given numeric changes in each measure and reflect the numeric changes in CO_2 emissions.
- **Choose several factors** affecting CO_2 reduction efficiency. We use TOPSIS to objectively evaluate these measures. This required adding different influencing elements to find each measure's effective factors.
- **Offer further measures** based on effective factors. Evaluate the effectiveness of the new measure.

2 Variables

Variable Symbol	Meaning	Variable Symbol	Meaning
C	The carbon dioxide emissions	E_m	Total energy for a life cycle
E_{in}	Energy input in a life cycle	θ_{ts}	Conversion Factors
A	The transaction matrix between industry sectors	CO_{2_i}	The carbon dioxide emission in year i
S_i	The sales of electronic device plant per year	$Elec$	Amount of electricity consumed each year
E_{ts}	The amount of energy type t consumed in sector s	CI	Carbon intensity
EC	Energy consumption	α	The constant term in multivariate model
β	The coefficient of sales in multivariate model	γ	The coefficient of energy consumption in multivariate model
σ	The coefficient of square of sales in multivariate model	Δt	The time delta is one day
Ep_{CO_2}	The carbon dioxide emissions from the production of chemical product i	Ec_{CO_2}	The fossil fuel combustion carbon dioxide emissions
Ei_{CO_2}	The waste incineration carbon dioxide emissions	PP_i	The annual production of chemical product i
EE_i	The carbon dioxide emission factor for product i	GAF	Geographic adjustment factor
C_{fuel}	The fossil fuel combustion	μ_{CO_2}	The fossil fuel carbon content
SW_i	The mass of waste plastics incinerated	dm_i	The dry matter content of waste plastics
CF_i	The carbon content of the waste plastics	FCF_i	The fossil-derived carbon content of the waste plastics
OF_i	The oxidation factor	$ECOF_i$	Energy consumption per year

Table 1: **Variables Table**

3 Assumptions and Justifications

3.1 Assumptions

- **Assumption**: We assume the factory to be a typical representation of factories in China. Then, based on the data analysis of China, we could build models expressing a quantitative relationship between economic growth, energy consumption, and CO_2 emissions[10].

- **Assumption**: We assume that the reduction in carbon emissions achieved by the factory through the reduction of employees only considers the emissions within the factory.

- **Assumption**: The default raw materials for plastic production are locally sourced, without considering the reduction in carbon emissions that could be achieved by using imported raw materials.

3.2 Justification

- **Justification**: The given problem document measures the electronic device sales from 2020 to 2023 using RMB (China Yuan). Therefore, we can assume the factory to be located in China.
- **Justification**: In schemes to reduce the workforce, the carbon emissions of workers are primarily composed of daily emissions.
- **Justification**: In factories, the sourcing of raw materials for plastic production is often quite complex. However, for the sake of simplifying our model, we only consider domestic raw materials.

4 Effectiveness Evaluation

4.1 Reduction of Site Area

4.1.1 Interpretation

The cellular manufacturing line surpasses the sequential production line with the benefits of time and space efficiency. It saves money and resources by manufacturing in smaller batches. We focus on factory space and carbon dioxide emissions as linear manufacturing shifts to cellular manufacturing. Less industrial areas require fewer resources, resulting in decreased operational costs (labor payment, water, electricity, and gas) and carbon dioxide emissions.

We use a life cycle approach to calculate emissions per $10m^2$ to determine the relationship between plant size and carbon dioxide emissions. Figure 1 shows four industrial land-use stages: Manufacturing, Construction, Operation, and Demolition. Each stage uses energy and emits CO_2. Then, we estimate carbon dioxide emissions over the factory's land usage lifetime.

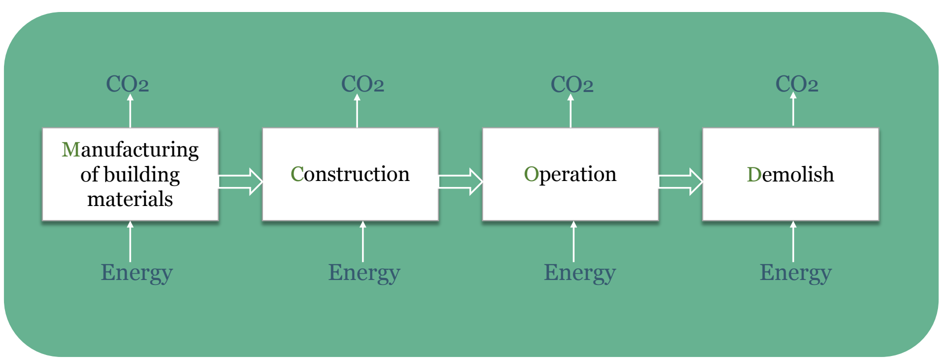

Figure 1: Flow Chart of Life Cycle

4.1.2 Model

The carbon dioxide emissions can be represented using an energy input-output model [13](Miller and Peter 1985). The energy intensity, which economically supports the total energy demand for a unit currency value of final demand, can be calculated using the following equation:

$$E_m = E_{in} \times (I - A)^{-1} \quad (1)$$

In equation 1, the embodied energy intensity vector represents the total energy required to meet the final demand presented to sector i in terms of dollars $(E_{m1}, E_{m2}, E_{m3}, ..., E_{mn})$; E_{in} $((E_{in1}, E_{in2}, E_{in3}, ..., E_{inn}))$ is an input vector; I is the unit matrix; The input-output table A is the transaction matrix between industry sectors.

$$W = \sum_{ts} E_{ts}\theta_{ts} \quad (2)$$

The CO_2 conversion factor can be expressed by equation 2, and the total CO_2 emissions for each industrial sector can be computed using equation 3. Similarly, the model is applied to calculate the CO_2 emissions for each building material during manufacturing.

$$C = W \times E_m = [W \times E_{in}(I - A)^{-1}] \quad (3)$$

$E_t s$ represents the amount of energy type t consumed in sector s; θ_{ts} denotes the conversion coefficient, and C represents the CO_2 emissions of two for each industry sector (in tons-dollars).

4.1.3 Data Collection

According to the Seo[14], the carbon dioxide emissions in the manufacturing and construction Stage are calculated by multiplying the weight of each building material by the previously determined carbon dioxide emission intensity sum. The CO_2 emissions due to energy conservation of each material are then considered, shown in the table 2.

Material	The amount use of materials $(kg/10m^2)$	The unit amount of CO_2 emitted $(kg - C/kg)$
Concrete	1058.0	0.054
Steel	31.0	0.425
Brick	151.4	0.011
Glass	2.0	0.750

Table 2: The CO_2 Emissions of each Material

During the Operation Stage, to convert the analysis results into carbon dioxide emissions, the CO_2 conversion factor is multiplied by the consumption of two types of energy. The CO_2 conversion factors used in this study are presented in Table 3.

Energy type	Conversion factor
LPG (ton-C/ton of oil equivalent)	0.713
City gas (ton-C/ton of oil equivalent)	0.637
Electricity [ton-C/(kWh)]	0.230
Heavy oil (ton-C/ton of oil equivalent)	0.875

Table 3: Conversion Factors for Different Energy Types

According to Thomas et al. (1996)[11], 51.5 MJ/m of energy as diesel fuel was needed to demolish a building typed as in situ concrete. To convert this value into final CO_2 emissions, the CO_2 conversion factor in Table 3 was multiplied. Using this value, the level of CO_2 emissions from the demolition process is $10.3kg - C/m^2$.

Stage	CO_2 Emissions
Manufacturing and Construction	408.5 $(\mathrm{kg-C})$
Operation	503.9 $(\mathrm{kg-C/10m^2year})$
Demolition	10.3 $(\mathrm{kg-C})$

Table 4: CO_2 Emissions at Different Stages

4.1.4 Results

Table 4 shows the carbon dioxide emissions per square meter in different stages. Thus, the total carbon dioxide emissions for one year of $400m^2$ area deduction is **36.908t**, which can be calculated based on the life cycle approach as follows:

$$C = \frac{A \times (S_1 + S_2 + S_3 + S_4)}{10} = \frac{400 \times (408.5 + 503.9 + 10.3)}{10} = 36.908(t) \tag{4}$$

4.2 Reduction of Labor

4.2.1 Interpretation

The amount of labor always has a considerable impact on carbon dioxide emissions. During the work in the electronic device plant, the workers consume many resources, which produce a lot of CO_2. This problem reduces labor needs due to higher productivity, leading to the workforce dropping from 100 to 50—this reduction of labor accounts for half of the initial workforce. Therefore, we must determine how this massive labor reduction affects factory carbon dioxide emissions.

4.2.2 Model

To calculate the reduced carbon emission by reducing labor from 100 to 50, we integrated three main aspects of labor-consuming resources into our carbon emission model to get the annual carbon emission per person. The three aspects are catering expenses, the use of electricity, and commutation.

During the conversion,we use Carbon intensity (CI) to convert KWh of electricity to kg of CO_2. Carbon intensity (CI) is the pollutant emission rate relative to an activity or industrial production process. The model to estimate the effect of reduction of labor would then be:

$$CO_{2Elec} = Elec \times CI \tag{5}$$

$$\Delta CO_2 = \Delta n \times (CO_{2cater} + CO_{2Elec} + CO_{2commute}) \tag{6}$$

4.2.3 Data Collection

The data on annual carbon emission in catering per person was obtained from the Chinese Journal of Food Hygiene [12]. The data of the annual network was obtained from the Electric Power Technology China network (eptchina. com)[9]. The data of carbon intensity was obtained from [2]. The commutation carbon emission is obtained from the China Clean Development Mechanism Fund[8].

$CO_{2cater}(kg)$	$Elec(KWH)$	$CI(kg/KWH)$	$CO_{2Elec}(kg)$	$CO_{2commute}(kg)$	Δn	$\Delta CO_2(t)$
497.4	787	0.4	314.8	280.0	50	54.6

Table 5: Data Collection and Results of Measure 2

4.2.4 Results

Hence, the total annual carbon emission per person is (497.4+314.8+280.0) Kg CO_2, about 1092.2 Kg CO_2.

Therefore, the total reduction of carbon emission due to the reduction of 50 people is (1092.2Kg $CO_2 \times 50$), which is about **54.6 tons** of CO_2.

4.3 Provision of Comfortable and Cost-efficient Working Conditions

4.3.1 Interpretation

The third measure, provision of comfortable and cost-efficient working conditions, mainly focuses on creating a comfortable workplace, such as redesigning production plant workstations and adding air conditioning. This measure can improve employee well-being and indirectly reduce CO_2 emissions.

The link chain of improved working conditions to environmental benefits can be formed, "Comfortable environment $\rightarrow$ Better well-being $\rightarrow$ Higher productivity $\rightarrow$ Improved product quality $\rightarrow$ Reduced resource usage $\rightarrow$ Energy savings $\rightarrow$ CO_2 emission reduction".

4.3.2 Model

After understanding the qualitative relationship, we need to quantify how more comfortable and cost-efficient working conditions reduce carbon dioxide emissions. Better working conditions affect annual sales and energy use. Therefore, with the provided data on changes in sales and energy consumption per year, we need to find the correlation model between sales and energy consumption and carbon dioxide emissions.

Since we do not have much direct data on carbon dioxide emission from the electronic device plant, we need to convert the data on sales (S) or energy consumption (EC) to the amount of CO_2. Using the models below, where i refers to the year:

$$CO_{2_i} = \begin{cases} S_i \cdot CI_s & \text{(Conversion from sales to CO}_2\text{)} \\ EC_i \cdot CI_{EC} & \text{(Conversion from energy consumption to CO}_2\text{)} \end{cases} \tag{7}$$

From this model 7, carbon emissions are calculated using carbon intensity; the results reflect a direct linear relationship with sales or energy consumption, representing the univariate model. For enhanced accuracy, we consider using a multivariate model, finding the relationships between two independent variables, sales and energy consumption, and one dependent variable, CO_2 emission.

In order to analyze the three variables' relationship and predict the CO_2 emissions, we estimated the following model[10][6], where the value of sales, energy consumption, and CO_2 emissions are converted to logarithm form, where i refers to the region, t refers to the time:

$$\ln(CO_2)_{i,t} = \begin{cases} \alpha_l + \beta_l \cdot \ln(S)_{i,t} + \gamma_l \cdot \ln(EC)_{i,t} & \text{(Linear relationship)} \\ \alpha_{non} + \beta_{non} \cdot \ln(S)_{i,t} + \gamma_{non} \cdot \ln(EC)_{i,t} + \sigma_{non} \cdot \ln(S^2)_{i,t} & \text{(Nonlinear relationship)} \end{cases} \tag{8}$$

4.3.3 Data Collection

The data of carbon intensity in grams of carbon dioxide per 1 kilowatt of power expended for 1 hour (g/KWH) in China and carbon intensity in kilograms per U.S. dollar was obtained from Statista [2][1]. The data on sales and energy consumption from 2020-2023 was obtained from the problem document. The data of exchange rate is obtained from Statista [3]. The data of coefficient factors (β,γ, σ are get from previous research papers [17][10][6]).

4.3.4 Results

By substituting the data of CI in the model 7, we can gain the specific reduction amount of carbon emission. Since the coefficient parameters of sales are all set in USD in the models, we use the exchange rate of 0.14 USD/CNY to convert the given sales in RMB to dollars. The collected data and results are integrated in the table below:

$Year$	$S(RMB)$	$S(\$)$	$EC(KWH)$	$CI_S(kg/\$)$	$CI_{EC}(g/KWH)$	$CO_{2_S}(t)$	$CO_{2_{EC}}(t)$
2020	58,100,000	8,134,000	1,670,000	0.40	531.15	3,254	887
2021	60,495,000	8,469,300	1,760,000	0.40	531.15	3,388	935
2022	73,100,000	10,234,000	1,580,000	0.40	531.15	4,094	839
2023	69,120,000	9,676,800	1,400,000	0.40	531.15	3,871	744

Table 6: Estimations of CO_2 Emission based on Carbon Intensity (CI)

The table highlights the difference in carbon dioxide estimates from the CI of sales and energy consumption. To initialize our multivariate model, we must choose the CO_2 emission between 3254t and 887t. Considering our electronic device plant's small size, with only 100 employees and a 100 square meter area, we selected 887 tons as the CO_2 emission in 2020.

Then, we use multivariate models to get more accurate effect of change in sales and energy consumption have on carbon emission. To use the multivariate model, we first convert the value of sales and energy consumption to logarithm form.

Next, we consider the linear relationship in a multivariate model. From María's article [10], the coefficient of sales and energy consumption are tested using data in China from 2010-2018. We then assign the constant term -7.83 to make the CO_2 consumption 887 tons. The coefficient parameter and the calculated results are shown below, referring to the first result for linear relationships in multivariate models.

$Year$	$\ln(S)$	$\ln(EC)$	α_1	β_1	γ_1	$\ln(CO_2)_1$	$CO_{2_1}(t)$	$\Delta CO_{2_1}(t)$
2020	15.91	14.33	-7.83	-0.36	1.42	6.79	887	
2021	15.95	14.38	-7.83	-0.36	1.42	6.85	942	55
2022	16.14	14.27	-7.83	-0.36	1.42	6.63	755	-187
2023	16.09	14.15	-7.83	-0.36	1.42	6.47	649	-106

Table 7: First Results for Linear Relationship in Multivariate Models

We use another set of coefficients with the same model, obtained from Shaohui and Tian [17]—the article extracts data from the China Statistical Yearbook and China Energy Statistical Yearbook. The economic growth, energy consumption, and CO_2 emissions were tested using data between 2000–and 2017, rejecting the unit root null hypothesis. The constant term is set to let the CO_2 carbon emission be 887t. The coefficient parameter and the calculated results are shown below, referring to the second result for linear relationships in multivariate models.

$Year$	$\ln(S)$	$\ln(EC)$	α_2	β_2	γ_2	$\ln(CO_2)_2$	$CO_{2_2}(t)$	$\Delta CO_{2_2}(t)$
2020	15.91	14.33	-7.54	0.96	0.04	6.79	887	
2021	15.95	14.38	-7.54	0.96	0.04	6.84	934	47
2022	16.14	14.27	-7.54	0.96	0.04	6.74	848	-86
2023	16.09	14.15	-7.54	0.96	0.04	6.63	754	-94

Table 8: Second Results for Linear Relationship in Multivariate Models

The nonlinear multivariate model enables us to determine the impact of GDP on CO_2 emissions at various energy consumption levels. The set of coefficients is obtained from Kizito [6], doing data analysis of Gross domestic product during 1990–2014 obtained from the World Development Indicators. The coefficient parameter and the calculated results are shown below:

$Year$	$\ln(S)$	$\ln(EC)$	$\ln(S^2)$	α_3	β_3	γ_3	σ_3	$\ln(CO_{2_3})$	$CO_{2_3}(t)$	$\Delta CO_{2_3}(t)$
2020	15.91	14.33	31.82	-8.76	-0.18	1.29	-0.001	6.79	887	
2021	15.95	14.38	31.9	-8.76	-0.18	1.29	-0.001	6.85	942	55
2022	16.14	14.27	32.28	-8.76	-0.18	1.29	-0.001	6.67	791	-151
2023	16.09	14.15	32.17	-8.76	-0.18	1.29	-0.001	6.53	684	-107

Table 9: Results for Nonlinear Relationship in Multivariate Models

Finally, we need to compare the calculated amount of carbon dioxide emission by three models. We calculate the mean values of decreased CO_2 emissions in the first results of the linear multivariate model.

$$\overline{\Delta CO_{2_1}} = \frac{1}{n} \times (\Delta CO_{2_{1_{2021}}} + \Delta CO_{2_{1_{2022}}} + \Delta CO_{2_{1_{2023}}}) = \frac{1}{3} \times (55 - 187 - 106)(t) \approx -79.3(t) \tag{9}$$

With the same method, we calculate the mean change values of deduction of CO_2 in the second and third results. We can get $\overline{\Delta CO_{2_2}}$ to be -44.3t and $\overline{\Delta CO_{2_3}}$ to be -67.7t, calculate again the mean value to get the decreased CO_2 amount each year.

$$CO_{2_{mean}} = \frac{1}{n} \times (CO_{2_1} + CO_{2_2} + CO_{2_3}) = \frac{1}{3} \times (-79.3 - 44.3 - 67.7)(t) \approx -64(t) \tag{10}$$

The two results show that β, the coefficient for energy consumption, is always positive and significant, showing that less energy consumption can lead to a significant deduction of CO_2. Due to the cost of building a more comfortable environment in 2021, the CO_2 emission increased. Then, with the constant deduction of 180 KWH per year, the CO_2 decreases.

For the coefficient of sales, it can be positive or negative. So, more sales can lead to an increase or decrease in CO_2 emission. These results fit the Environmental Kuznets Curve (EKC) hypothesis [6], where increased economic conditions can lead to an increase or decrease or CO_2 before and after the turning point.

The final results of deduction of carbon dioxide using measure 3 is **64tons** per year.

4.4 Reduction and Recycling of Packaging Materials

4.4.1 Interpretation

The fourth method presented involves reducing and recycling packaging materials. In this section, we employ a life cycle approach to establish a comprehensive carbon emission accounting model for plastics across six stages: fossil raw material extraction, processing, cracking, polymerization, injection molding, and non-plastic disposal.

Then, we calculate carbon dioxide emissions per ton of plastic using 2018 Chinese plastics production, consumption, and disposal data. Finally, we use this model to evaluate how the fourth measure, reducing and recycling packaging, reduces CO_2 emissions at an electronic device manufacturing facility.

4.4.2 Model

In this model, we adopt a full life cycle approach to accounting for the holistic process of plastic carbon emissions, with the system boundary including plastic production, consumption, and waste disposal. The six stages of plastic life cycle is shown in the illustration of plastic life cycle.

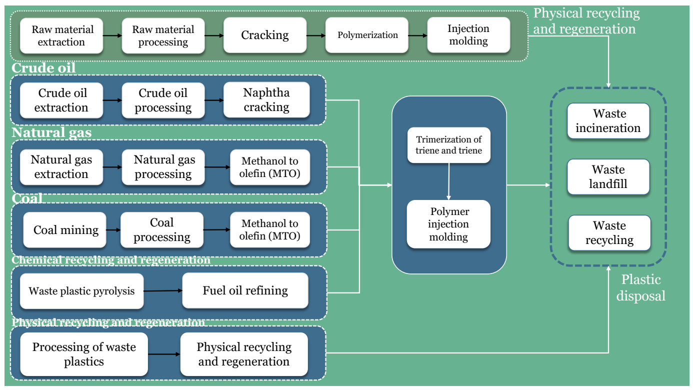

Figure 2: Illustration of Plastic Life Cycle

Among them, we analyzed the carbon emission produced for industrial processes, fossil fuel combustion and plastic waste recycle and of raw materials (crude oil, natural gas, coal) to the manufacture of plastic products in factories.We only considered carbon emissions in the "territorial emissions" scope, so emissions from export and import are not considered.

Within the life cycle, the first five are all part of the plastics production stage, and carbon emissions are highly correlated with the production process routes. The production stage consists of five main production routes below. After being extracted, 'triene triphenylene' is polymerized and injection molded into plastic products:

- The first is the production route using crude oil as raw material. Starting from crude oil mining and processing, the organic raw material 'triene triphenylene' is polymerized into synthetic resin.
- Second, the production route is based on natural gas as a raw material; the methanol is converted into 'triene triphenylene.'
- Third, the production route is based on coal as raw material, starting from coal mining and processing, and the methanol is converted into 'triene triphenylene.'
- Fourth, the chemical recycling route, waste plastics cracked into fuel oil, fuel oil refining to 'triene triphenyl.'
- Fifth, the physical recycling route, waste plastics processing into synthetic resin, synthetic resin injection molding for plastic products.

The carbon emission framework we have developed includes three types of emissions: industrial process, fossil fuel combustion and plastic waste incineration. For waste plastic recycling routes, they are also categorized into industrial process emissions and fossil fuel combustion emissions for calculation, as they have the same carbon emission generation mechanism as that of the plastic production stage.

The methodology for accounting for these different types of emissions is derived from the 2006 IPCC Guidelines for National Greenhouse Gas Inventories published by the Intergovernmental Panel on Climate Change (IPCC)[5].

- Carbon emission accounting method for industrial processes. The model can be calculated based on the activity data of petrochemical and chemical production and the emission factors of the production process.
$$Ep_{CO_2} = PP_i \times EE_i \tag{11}$$

- Methodology for accounting carbon emissions from fossil fuel combustion. Using the emission factor method, with the specific calculation formula shown below:
$$Ec_{CO_2} = C_{fuel} \times \mu_{CO_2} \tag{12}$$
The formula defaults to a fuel carbon oxidation rate of 100%. "Fuel consumption" needs to be differentiated by fuel type, and the physical quantity and low-level calorific value parameter ($\mathrm{TJ/t}$ or $\mathrm{TJ/m^3}$) of each fuel are the key data.

- Methodologies for accounting carbon emissions from waste incineration. It is calculated using the formulae shown below:
$$Ei_{CO_2} = \textstyle\sum_i (SW_i \times dm_i \times CF_i \times FCF_i \times OF_i) \times \frac{44}{12} \tag{13}$$
$\frac{44}{12}$ is the mass conversion relationship between carbon dioxide and carbon.

4.4.3 Data Collection

We get the data of the proportion of coal, petroleum, and natural gas consumption required for plastic production to the total extraction volume based on the "China Energy Statistical Yearbook."

Key parameters in industrial processes include methanol production based on natural gas production, using information from the China Petroleum and Chemical Bulk Products Annual Report (2020 version).

The data provided in the GHG Accounting and Reporting Guidelines for Enterprises in China were also used in the calculations. According to the literature research[15].

Energy types are determined based on research data, referencing the energy consumption types used as fuel in typical refining enterprises. Methanol emission factors are calculated based on default values from the IPCC guidelines $0.67\,\mathrm{t\,CO_2/t\,methanol}$ for natural gas production and referenced literature for coal production. The carbon emission factor in the industrial process is $2.55\,\mathrm{t\,CO_2/t\,methanol}$[16].

Energy types are determined based on research data. Parameters for naphtha cracking are calculated using default values from the IPCC guidelines $1.73\,\mathrm{t\,CO_2/t}$ ethylene with a geographical adjustment factor of 100%.

Waste plastics have a carbon content of 0.75, with all of it being fossil-derived. Fossilized carbon content of waste plastics is 1, and the complete combustion efficiency of the incinerator is 0.95.

4.4.4 Results

After using the three models stated above, the calculated results of CO_2 emissions is shown in the table below:

	Coal	Crude Oil	Natural Gas	Chemical Recycling	Physical Recycling	Average
CO_2 Emissions (tons per ton of plastic production)	12	8.1	8.5	6.1	1.5	7.2

Table 10: Table of Carbon Dioxide Emissions Related to Plastic Production Process

The table shows that coal, petroleum, natural gas, and recycled waste plastics are the main plastic production raw materials. The coal-based plastic production route emits the most carbon per unit. However, physical recycling of waste plastics only emits $1.5\,\mathrm{t\,CO_2/t}$. This reduction in emissions by 12.5% and 18.5% compared to coal-based and crude oil-based plastic production routes is a significant advantage in the low-carbon transformation of the plastic industry chain. Saving 1.1t plastics reduces carbon emissions by **7.92 t**. We draw a histogram below to show how plastic production processes affect carbon dioxide emissions:

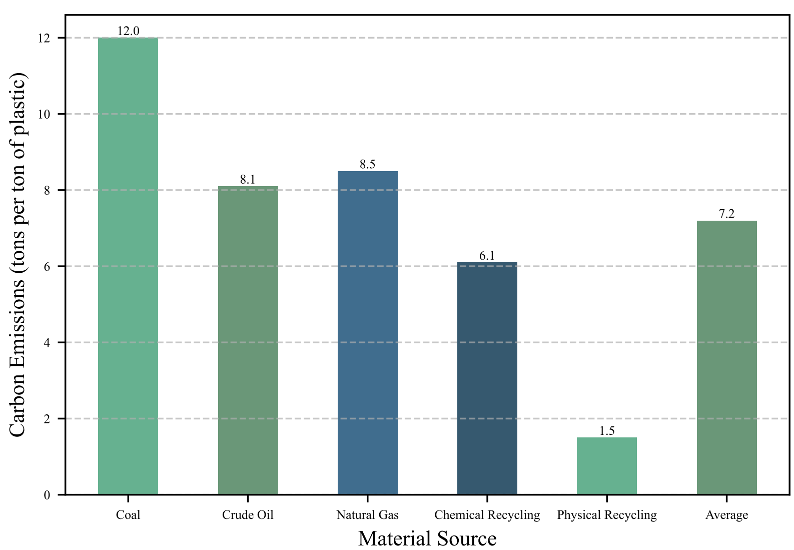

Figure 3: Histogram of Carbon Dioxide Emissions Related to Plastic Production Process

4.5 Overall Effectiveness Evaluation

In conclusion, reducing site area M_1, labor M_2, working conditions M_3, and packaging materials has reduced annual carbon emissions M_4.

Measure	Reduced Carbon Emission (each year/tons)	Reduced Carbon Emission %
M_1	36.9	22.57%
M_2	54.6	33.40%
M_3	64	39.14%
M_4	8	4.90%

Table 11: The CO_2 Emissions for each Measure

In the graph below, these green initiatives reduced carbon emissions by 22.57%, 33.34%, 39.14%, 4.90% shown in the table 11. This holistic strategy emphasizes resource efficiency, ecological sustainability, and environmental responsibility. These solutions provide a comprehensive and effective approach to reducing operational carbon emissions.

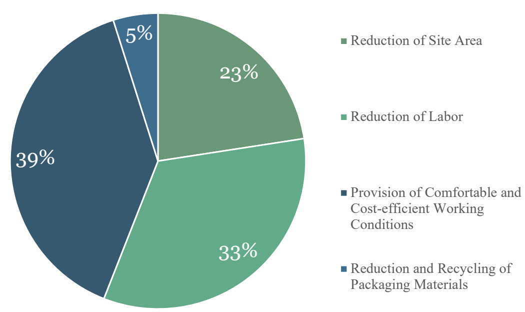

Figure 4: Graph of carbon emissions in each measure

5 TOPSIS for Effectiveness of Measures

5.1 Introduction to TOPSIS

TOPSIS, a technique for Order of Preference by Similarity to Ideal Solution[4], is a technique employed in the process of making decisions that involve several factors. It aids in assessing and choosing the optimal option from a provided array of choices. The technique is based on the assumption that the best decision is the one that is closest to the positive ideal solution (i.e., the choice that maximizes the criteria) and farthest from the negative least ideal solution (i.e., the choice that reduces the criteria).

In order to execute the method, a pre-defined set of criteria is first established. Afterwards, weights are assigned to each criterion based on their individual importance. Subsequently, a matrix is built including all the available choices and criteria. The matrix is standardized to account for discrepancies in the magnitude of the criterion. In the end, the closeness of each choice to the desired ideal solution is evaluated by calculating the distance between them, and the options are then ranked based on this assessment.

5.2 TOPSIS for Measures' Effectiveness

Two criteria assess four measures: the reduction of carbon dioxide emissions and the reduction of coal. The TOPSIS technique is used to rank the measures, and the strategy that results in the greatest reduction in CO_2 and coals is regarded as the most effective in reducing carbon dioxide emissions.

- **Normalization**: Prior to evaluating the data, the TOPSIS normalizes the dataset. Here, x_{ij} refers to the element located at the i_{th} row and j_{th} column of the dataset. Owing to the distinct range between two index-deduction of carbon dioxide emissions and deduction of coal, we standardize the relationship between the two by normalization. The normalization process is shown in the following equation.

$$n_{ij} = \frac{x_{ij}}{\sqrt{\sum_{i=1}^{m} x_{ij}^2}}(i = 1, 2, 3, 4.j = 1, 2) \tag{14}$$

- **Weighting**: Since each evaluation criterion holds a different weight in real-world scenarios, in the weighting step, we divide each normalized data by its corresponding weight to obtain weighted data as shown in the equation below. This step is crucial as the determination of weights is highly relevant. Therefore, we investigate the variation in the ranking of evaluation criteria under different weight proportions.

$$v_{ij} = w_i \times n_{ij}, (i = 1, 2, 3, 4, j = 1, 2) \tag{15}$$

- **Best and Worst**: Taking into account these preliminary factors, the formulas are created to determine the best A^+ and worst A^- for each measure in two factors separately.

$$A^+ = \left\{v_1^+, ..., v_n^+\right\} = \{(\max v_{ij}/i \in I), (\min v_{ij}/i \in J)\} \tag{16}$$
$$A^- = \left\{v_1^-, ..., v_n^-\right\} = \{(\min v_{ij}/i \in I), (\max v_{ij}/i \in J)\} \tag{17}$$

- **Distance Calculation**: Afterward, we calculate the distance(variance) of the data relative to the column's maximum and minimum values by computing the average of the mean squares. The variance relative to the maximum value is denoted as $d+$ and the variance relative to the minimum value is denoted as $d-$ shown in the following equations:

$$d_i^+ = \left\{\sum_{j=1}^{n}(v_{ij} - v_j^+)^2\right\}^{\frac{1}{2}}, i = 1, 2 \tag{18}$$
$$d_i^- = \left\{\sum_{j=1}^{n}(v_{ij} - v_j^-)^2\right\}^{\frac{1}{2}}, i = 1, 2 \tag{19}$$

- **Score**: The final score R_i for the four options is calculated by dividing $d+$ by $d-$ as the equation below.

$$R_i = \frac{d_i^-}{(d_i^+ + d_i^-)}, 0 \leq R_i \leq 1 \tag{20}$$

- **Ranking**: All results are taken and ranked according to R_i, and the highest ranking overall option is chosen along with the highest deduction of carbon dioxide emissions and deduction of coal

5.3 The "Best Measures" by TOPSIS

The findings are obtained from the preceding TOPSIS method. The original measures and their corresponding reductions in CO_2 emissions and coal usage are shown in two different matrices.

$$\begin{bmatrix} 37 & 16.4 \\ 54.6 & 23.9 \\ 64 & 0.025 \\ 8 & 0.44 \end{bmatrix} \xrightarrow[Normalization]{} \begin{bmatrix} 0.4 & 0.6 \\ 0.5 & 0.8 \\ 64 & 0.0 \\ 0.1 & 0.0 \end{bmatrix} \tag{21}$$

By employing the weighting equation 15, with carbon dioxide emissions carrying a weight of **0.7** and reduction in coal-carrying a weight of **0.3**, we can calculate the disparity between the best and worst outcomes. This allows us to determine the ranking of these four measures based on the specified weights.

Measures	Judging Index	Ranked
Reduction of Site Area	0.7	2
Reduction of Labor	0.9	1
Provision of Comfortable and Cost-efficient Working Conditions	0.2	3
Reduction and Recycling of Packaging Materials	0.0	4

Table 12: Measures and Rankings with Weights of 0.7 CO_2 Emissions and 0.3 Reduction of Coal

Thus, based on the provided weight table, it is evident that reducing labor is the most effective approach to decreasing CO_2 emissions. On the other hand, the actions involving the reduction and recycling of packaging materials have the lowest index and are the least successful.

5.4 The Sensitive Analysis of TOPSIS Model

One of the most significant uncertainty factors in TOPSIS model is the weighting factor between the reduction of CO_2 emissions and coal, which is assumed to be $0.7CO_2 : 0.3$ coal in our model.

To test and analyze the sensitivity of the model proposed, the weighting factor is changed from $(0.1 : 0.9) - (0.9 : 0.1)$, increasing by increments of $(+0.2, -0.2)$.

Despite the small alterations in the evaluation criteria, the overall ranking remained quite stable. Significantly, the last measure remained unchanged, as seen in Figure 5. This showcases the dependability and consistency of TOPSIS, hence affirming the dependability and consistency of its evaluation of the effectiveness of measures.

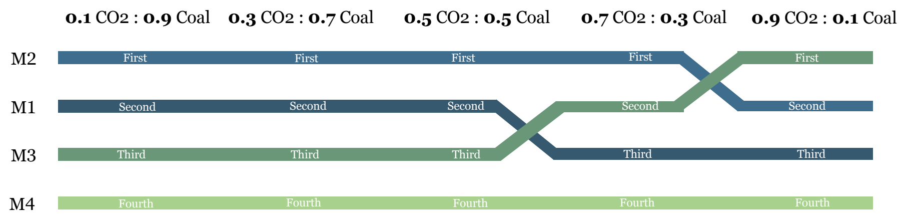

Figure 5: Sensitive Analysis of TOPSIS Model

6 Bicycle Commuting

6.1 Interpretation

In a thorough analysis of the four carbon reduction strategies mentioned above, it has been observed that strategies targeting human behavior tend to yield more significant carbon reduction effects. Building upon the recognition of the importance of human behavior, we propose a sustainable initiative — transitioning employees from traditional fuel-powered commuting to bicycle commuting.

6.2 Data Collection

To quantify the potential impact of transitioning to bicycle commuting, findings from the "2023 Commuting Monitoring Report for Major Cities in China" reveal that the average commuting distance in Beijing is 11.7 kilometers. Based on this, we assume that employees of this electronic equipment factory commute an average distance of 11.7 kilometers per day for 250 working days per year[7]. By calculating carbon dioxide emissions and energy consumption per kilometer of fuel burned, conventional fuel-powered vehicles produce approximately 141.7 grams of carbon dioxide per kilometer and consume about 8.71 kilograms of standard coal energy per kilometer. Based on this conservative estimate, the proposed transition for 50 employees in the factory could result in a significant annual reduction of approximately **20 tons of CO_2** emissions. Additionally, the associated energy savings are equivalent to around 1273 tons of standard coal.

6.3 Conclusion

In conclusion, transitioning employees from fuel-powered commuting to bicycle commuting is a practical and impactful approach, supported by objective energy savings data. This aligns with the United Nations' 17 Sustainable Development Goals, specifically the goal of combating climate change. Beyond environmental benefits, employees engaging in bicycle commuting positively impact their health and well-being, fostering a more dynamic and resilient workforce. Furthermore, employees stand to benefit from personal cost savings, while the company may see reduced expenses related to parking facilities and carbon offset initiatives. By adopting this strategy, we not only significantly contribute to carbon reduction but also promote a healthier, more sustainable work environment, perfectly aligning with modern corporate responsibility. The overall results compared to the prior measures are shown in Table 13.

Measures	Judging Index	Ranked
Reduction of Site Area	0.5	4
Reduction of Labor	0.7	3
Provision of Comfortable and Cost-efficient Working Conditions	0.8	2
Reduction and Recycling of Packaging Materials	0.0	5
Bicycle Commuting	1.0	1

Table 13: Measures and Rankings with Weights of 0.9 CO_2 Emissions and 0.1 Reduction of Coal

7 Model Strengths and Weakness

7.1 Strengths

- **Reduction of Site of Area**: This model employs life cycle assessment to compute carbon emissions throughout building site development. It also extensively examines carbon emissions from different materials and surface regions. Carbon dioxide emissions are calculated more thoroughly.

- **Reduction of Labor**: In reducing the carbon emissions generated by employees, we have considered several core factors that affect employee carbon emissions, including diet, commuting, and electricity usage. In our model, these factors are crucial in determining employee carbon emissions, so our final data calculations are very close to actual values. Additionally, we have taken into account the average situation in China, so the data is universal.

- **Provision of Comfortable and Cost-efficient Working Conditions**: The models built in measure three use an invariant and a multivariate model to investigate the combined effects of change in sales and energy consumption on the change of CO_2. Besides, we use linear and nonlinear relationships in multivariate models to find the modeled CO_2 emissions in three models. By calculating average changes of CO_2 per year in three models, we calculate the average value again to get a more accurate change in CO_2.

- **Reduction and Recycling Packaging Materials**: This model demonstrates a methodological rigor by adopting a comprehensive life cycle assessment to intricately scrutinize the ramifications of distinct phases within diverse production trajectories on carbon dioxide emissions. The factors under consideration exhibit a commendable breadth, as they undergo quantification based on authoritative literature from the Intergovernmental Panel on Climate Change (IPCC). It is noteworthy that the entirety of the data utilized is meticulously curated from official sources, thereby imbuing the findings with a heightened level of empirical veracity. Consequently, the derived carbon emission values manifest substantive reference utility.

- **TOPSIS Evaluation**: Comparing to the entropy weighting method, TOPSIS has advantages lies in its objectivity by analyzing the evaluation results solely from the perspective of data itself. The results obtained are therefore based on the data alone.

7.2 Weaknesses

- **Reduction of Site of Area**: The model did not take into account the relationship between different energy consumption and the number of personnel during factory operation, leading to the possibility of carbon dioxide emissions in the model being less than the actual values in the real world.

- **Reduction of Labor**: We assume that the carbon emissions reduction achieved by reducing the workforce in factories only considers the emissions reduction within the factory. Therefore, when calculating the emissions reduction brought about by reducing the workforce, our model does not consider the emissions reduction outside the company.

- **Provision of Comfortable and Cost-efficient Working Conditions**: Although we use various models, the accurate change value in CO_2 is still hard to estimate. The considerably different values obtained from the three models make us unsure about the accurate decrease of CO_2 emissions using measure 3.

- **Reduction and Recycling Packaging Materials**: Regrettably, the model evinces a notable limitation by omitting consideration of the geographical provenance of raw material production and its consequential impact on carbon dioxide emissions. The presumption of a local provenance for all raw materials requisite for plastic production constitutes a simplifying assumption that may undermine the model's ecological fidelity. Moreover, the absence of production proportion data for divergent routes results in the direct implementation of an arithmetic mean to consolidate carbon emissions across distinct production trajectories. This averaging approach may potentially introduce an oversimplification bias, curtailing the nuanced precision of the model's estimations.

- **TOPSIS Evaluation**:

  The TOPSIS assessment model needs data relative relationships and subjective weights. Thus, TOPSIS outcomes combine subjective and objective elements, unlike objective assessment methods. Since weights are subjective data, conventional weight evaluation may give subjective weights. To offer a more full and objective understanding of scheme rankings, we compute and compare the ranks of the four schemes under different weights.

  Our subjective-objective evaluation method is solid, however we lack factor indicators. We analyze our model using carbon emission reduction and typical coal energy savings. During modeling, we found that several small characteristics impact these four systems' evaluation. These characteristics are hard to measure and don't effect all schemes, making modeling difficult. Therefore, our model does not account for these qualities, which is flawed.

  China's average statistics inform our methodology and data. Our model is worldwide, yet certain manufacturers may misinterpret it. Certain model parameters must be replaced for proper assessment.

8 Conclusion

To assess the effectiveness of the strategies said to reduce carbon dioxide, we developed four mathematical models that encompass physical, economic, ecological, and social factors, therefore accomplishing this objective.

Upon conducting a thorough analysis of the several phases of construction using the life cycle approach, we have verified that there would be a reduction of 36.9 metric tons in carbon dioxide emissions. Furthermore, we conducted a calculation to determine the reduction in carbon dioxide emissions resulting from labor reduction, taking into account three key factors: the carbon emissions associated with eating, commuting, and power consumption. Furthermore, we employ linear and nonlinear multivariate models to examine the collective impact of changes in sales and carbon assumption on alterations in CO_2 emissions, with the aim of providing pleasant and cost-effective working conditions. Measure 3 can reduce approximately 64 tons of CO_2 each year, resulting in the ultimate outcome. Lastly, utilizing the life cycle technique, we examine the carbon emissions associated with the various pathways and stages involved in the manufacture of plastics.

Subsequently, we assessed the effectiveness of these interventions using TOPSIS, revealing that the most efficient strategy for lowering CO_2 emissions is labor reduction. Therefore, we propose the development of a novel metric for bicycle commuting, which would provide significant environmental and social advantages. Ultimately, we have identified methods to impartially ascertain carbon emissions, assess the efficacy of each approach, and suggest efficient measures for reducing carbon emissions.

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9 Appendix A

x_{ij}	CO2	Coal	x_{ij}^2	$CO2^2$	$Coal^2$	n_{ij}	$CO2_{n_{ij}}$	$Coal_{n_{ij}}$
M1	37	16.4	1369	0.4	0.6	0.4	0.9	0.1
M2	48	23.9	2304	0.5	0.8	0.5	0.9	0.1
M3	64	0.025	4096	0.7	0.0	0.7	0.9	0.0
M4	8	0.44	64	0.1	0.0	0.1	0.9	0.0

Table 14: Sub-table 1 of TOPSIS Analysis in Appendix A

V_{ij}	$A+$	$A-$	d_{i+}	d_{i-}	Σd_{i+}	Σd_{i-}	Square Root d_{i+}	Square Root d_{i-}	R_i	Ranked
M1	0.4	0.7	0.1	0.1	0.3	0.3	0.5477	0.5477	0.5	3
M2	0.5	0.7	0.0	0.2	0.0	0.2	0.0000	0.4472	0.7	2
M3	0.7	0.7	0.0	0.3	0.0	0.3	0.0000	0.5477	0.9	1
M4	0.1	0.7	0.3	0.0	0.3	0.0	0.5477	0.0000	0.0	4

Table 15: Sub-table 2 of TOPSIS Analysis Table in Appendix A