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Research Article

Carbon Emission Influencing Factors and Scenario Prediction for Construction Industry in Beijing–Tianjin–Hebei

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In this paper, the factors causing the change in carbon emissions from direct energy consumption in the construction industry in Beijing–Tianjin–Hebei are decomposed using the logarithmic mean divisia index (LMDI) method to analyze the effect values and contribution rates of each macrofactor. Based on the decomposition results and given relevant national policies, five scenarios are set up for each influencing factor, and a regression stochastic impact on population, affluence, and technology (STIRPAT) with ridge regression analysis is applied to each scenario combination for scenario prediction, forming a scientific and reasonable theoretical system to predict the future time of carbon peaking and carbon neutrality in the construction industry of Beijing–Tianjin–Hebei. The results show that (1) energy intensity and energy structure have a suppressive effect on direct energy consumption carbon emissions in the construction industry in Beijing–Tianjin–Hebei, and the industrial structure, economy, and population will promote an increase in carbon emissions. Energy intensity and the economy have a more significant effect on carbon emissions in the construction industry. (2) The peak year of carbon emissions varies with different scenarios, and the energy efficiency scenario achieves peak carbon in 2028, the earliest peak time, and the lowest peak, as it is the optimal emission reduction projection scenario.

1. Introduction

The current increase in global greenhouse gas emissions has led to a continuous rise in temperature and a severe global warming problem. According to the IPCC in the "Special Report on Global 1.5°C Temperature Rise," if greenhouse gas emissions continue to increase, the global temperature could rise by 1.5°C from 2030 to 2052 [1]. As the world's second-largest energy consumer, China topped the world in carbon emissions in 2017, accounting for one-third of global carbon emissions [2]. As a member of the United Nations Framework Treaty on Climate Change (UNFCCC), China committed to increase its autonomous national contribution at the 75th UN General Assembly. In response to international pressure and to assume the responsibility of great power, China has committed to carbon emissions aiming for carbon peaking by 2030 and carbon neutrality by 2060.

The construction industry is a critical sector in China's energy consumption and a significant source of carbon emissions. The IPCC's Fifth Assessment Report states that one-third of the global end-use energy consumption comes from the construction industry, generating 25% of global greenhouse gas emissions [3]. Along with the progress of urbanization and the continuous growth of the economic level, China's urbanization rate is 63.89%, and the completed construction area would have reached 3.838 billion square meters by the end of 2020 [4]. Therefore, carbon emissions still show a growing trend in the future. Beijing–Tianjin–Hebei is the economic circle of China's capital city with critical economic zones and industrial clusters in North China. Its carbon emissions account for more than 10% of the national share, and its carbon emissions per unit GDP and unit population exceed the national average [5]. During the 12th 5-year plan period, urban buildings in Beijing–Tianjin–Hebei reached 100% energy-saving construction standards, but the added value of the construction industry was only 4.95% of GDP.

The construction industry in Beijing–Tianjin–Hebei must achieve carbon neutrality, as it is the largest populated area in the north and a vital demonstration area for achieving carbon neutrality. Therefore, this paper selects the construction industry in Beijing–Tianjin–Hebei as the research object to supplement and improve the research related to direct carbon emissions from the construction industry in this area given that it is the object and given the methodological perspectives and to propose more specific and feasible urban emission reduction policies. Second, in this paper, the logarithmic mean divisia index (LMDI) factor decomposition method and STIRPAT model are combined, and this model is subjected to ridge regression analysis to verify the environmental Kuznets hypothesis of economic growth, energy intensity, and carbon emissions, resulting in the energy intensity environmental Kuznets curve (EKC) model as the basic model with a good fitting effect and high prediction accuracy. Third, setting up five different scenarios for carbon emission prediction can fully consider the future direct carbon emission trends of the construction industry in Beijing–Tianjin–Hebei to obtain more scientific and reasonable prediction results, evaluating the optimal emission reduction scenarios and providing theoretical references for related studies in other developing countries or regions.

2. Literature Review

With the worldwide concern for environmental issues in recent years, carbon emissions from the construction industry have become an intensely debated issue for many scholars. Foreign scholars usually use the life cycle and input–output approaches to calculate carbon emissions. Kairies-Alvarado et al. [6] calculated carbon emissions from installing and constructing public buildings and building construction in Chile using the life cycle approach. Acquaye and Duffy [7] used the input–output approach to develop a carbon emission calculation model for the Irish construction industry. Christodoulakis et al. [8] used the input–output method to study Greece's future energy demand and carbon emission trajectory. Domestic scholars usually use the emission factor method to calculate carbon emissions. Shang et al. [9] selected four energy sources, namely coal, electricity, natural gas, and oil, and used the emission factor method to determine carbon emissions. Feng and Wang [10] measured the carbon emissions from the construction industry in 30 provinces in China and showed that the overall carbon emissions from the construction industry in each province showed an increasing trend year by year. Decomposing the direct carbon emission drivers of the construction industry mainly uses the LMDI factor decomposition method, Kaya constant equation, autoregressive distributed lag model, and the nonparametric additive regression model. LMDI was proposed by Ang [11] based on a comprehensive comparison of various index decomposition analysis (IDA) methods using the average index. LMDI has the advantage of enabling complete decomposition of the target variable, effectively solving the problem of 0 data values and negative values, in addition to the decomposition results not containing residual terms that are difficult to interpret. The results of the additive multiplicative method are consistent, so this paper chooses the LMDI factor decomposition method to decompose carbon emission impact factors. This method has been widely used in several countries, such as Turkey [12], Finland [13], Japan [14], and China [15–17], for energy consumption and carbon emission problems in the construction sector.

Most scholars believe that construction carbon emissions should focus more on the daily use and materialization phases. However, the carbon emissions generated during construction are small and can even be ignored under certain conditions [18]. Studies on the construction industry have mainly focused on aspects such as building construction and construction industry relevance [19, 20]. Few articles have analyzed the direct carbon emission impact factors and prediction of the construction industry at the macrolevel, as this is essential for analyzing the direct carbon emissions of the construction industry and predicting the time of the carbon peak in the region by combining indicators such as the output value and population in the construction industry, reflecting the macroenergy intensity and energy structure of the national economy. To better predict carbon emissions, the macrodrivers of direct carbon emissions from the construction industry must be selected for analysis and study. Zhou et al. [21] studied the effects of the economy, population, energy structure, and energy intensity on direct energy consumption and carbon emissions in the construction industry in Beijing–Tianjin–Hebei. Lai et al. [22] demonstrated that the building scale GDP influences the carbon emission intensity of the construction industry in China and that carbon emissions per unit area tend to decrease with economic growth. That energy intensity helps reduce carbon emissions [22]. In addition, Shi et al. [23] used structural decomposition to explore the contribution of the drivers of the construction industry. Similarly, they concluded that energy intensity contributed the most to carbon emissions throughout the study period [23], and Wang et al. [24] concluded that the suppressive effect of energy intensity on carbon emissions from the construction industry varied between provinces. Hatzigeorgiou et al. [25] decomposed carbon emissions in Greece into four drivers, income, energy intensity, energy mix, and population, and concluded that an increase in income could contribute to carbon emissions in the construction sector and that energy intensity can lead to a decrease in carbon emissions. Wang et al. [26] used system dynamics to study the dynamic characteristics of the economic growth rate, energy mix, and industrial structure on carbon emissions in the construction sector. A study of 41 countries worldwide suggested that the outflow of carbon emissions from the construction industry is mainly in the real estate and utilities sectors. The global construction industry should improve energy efficiency and upgrade the industrial structure to reduce carbon emissions [27]. Malaysian scholars have shown that resistance to low-carbon policies and lack of experience with low-carbon technologies can hinder carbon emission reduction in the construction industry [28].

Many scholars have studied peak carbon emissions and the timing of carbon peaking in the construction industry. Wakivams used scenario analysis to examine the carbon emission potential of the construction industry and concluded that electricity consumption could be reduced through energy efficiency and energy conservation measures [29]. Li et al. [30] explored the possibility of carbon peaking in China's construction sector from two perspectives, LMDI index decomposition and scenario prediction, and under the baseline scenario, they found that the construction sector reaches carbon peaking in 2045 and energy efficiency and building energy efficiency technology measures are needed if carbon peaking is to be achieved in 2030. Du et al. [31] used the system dynamics approach to predict the increasing trend of total carbon emissions and carbon intensity from 2011 to 2015 by assuming the influence of economic growth and policy factors on carbon emissions in the construction industry under different scenarios. Zuo et al. [32] and Fang et al. [33] used the STIRPAT model to show that China peaks in 2028–2014, with 2030 being the optimal peak year, where carbon peaking can be advanced by reducing energy intensity and optimizing the industrial structure.

In summary, most of the current studies have selected national [34], provincial [35], and municipal [36] as the research objects, and there are relatively few pieces of literature studying the macrodrivers of the decomposition of direct carbon emissions from the construction industry in urban clusters. In addition, although the current studies have made some achievements in carbon emission drivers and scenario analysis, the research methods and content are independent of each other in that they only use LMDI factor decomposition to calculate the contribution effect of drivers or only use the STIRPAT model for scenario prediction, without forming a complete research system. Based on the energy balance sheet of the Beijing–Tianjin–Hebei region in the China Energy Statistical Yearbook 2008–2021, this paper calculates the direct carbon emissions from nine types of energy sources in the construction industry of Beijing–Tianjin–Hebei, calculates the contribution rate of the driving factors by the LMDI factor decomposition method; moreover, the paper establishes a linear regression equation with a better fitting effect by using the STIRPAT model after ridge regression analysis to forecast and analyze the carbon emissions from macrofactors in the construction industry of Beijing–Tianjin–Hebei under different scenarios in the future and predicts its carbon peak time and peak value.

3. Data Sources and Research Methodology

3.1. Data Sources. The energy consumption data in this study were obtained from the "Regional Energy Balance Sheets" of Beijing, Tianjin, and Hebei in the China Energy Statistical Yearbook 2008–2021. Based on the possibility of data acquisition, eight representative primary energy sources, including coal, coke, gasoline, kerosene, fuel oil, and natural gas, are selected for the aggregation of direct carbon emissions. In recent years, the proportion of renewable energy generation in the construction industry in the Beijing–Tianjin–Hebei region has increased year by year, and the carbon emissions from construction electricity generated by such energy sources are not deducted in this paper. To reduce data bias due to inconsistent statistical paths, population and gross regional product are obtained from Beijing, Tianjin, and Hebei statistical yearbooks for the construction industry. In contrast, gross construction product is obtained from the 2008–2021 China Construction Industry Statistical Yearbook.

3.2. Research Methodology

3.2.1. Direct Carbon Emission Measurement. The construction industry is the construction sector referred to in China's input–output tables, including housing, civil engineering construction, building installation, building decoration, and other construction industries; direct carbon emissions from the construction industry refer to the energy consumed and carbon dioxide emissions released from the construction industry's activities during the design, production construction, and demolition phases. According to the IPCC Guidelines for National Greenhouse Gas Emissions Inventories, the direct carbon emissions from the construction sector in Beijing–Tianjin–Hebei from 2007 to 2020 are calculated with the following formula [37]:

$$C = \sum E_{it} \times \gamma_i \times \beta_i = \sum E_{it} \times \rho_i, \tag{1}$$

where C is the direct carbon emissions of the construction industry; E_{it} is the actual energy consumption of class i energy in the construction industry in year t; γ_i is the average low-level heat of energy, the unit is trillion joules per ton; $\beta_i = \mathrm{CEC}_i \times \mathrm{COF}$ is the average low-level heat generation of energy in trillion joules per ton, in which CEC_i is the carbon content in tons of carbon/trillion joules for the ith type of energy, and COF is the carbon oxidation factor. This paper assumes that various energy sources are fully combusted, so COF = 100%; $\rho_i = \gamma_i \times \beta_i$ is the carbon emission factor. According to the 2006 IPCC Guidelines for National Greenhouse Gas Inventories and the China Energy Statistical Yearbook, nine energy sources' average low-level heat generation is used to calculate the carbon emission factors and coefficients, as shown in Table 1.

3.2.2. LMDI Factor Decomposition Model. The factor decomposition method calculates drivers' contribution to energy consumption or carbon emissions by decomposing energy consumption or carbon emissions into multiple drivers and quantitatively analyzing the changes in each driver. It mainly includes IDA and structural decomposition analysis (SDA). Both decomposition methods can be used to analyze the contribution effect of drivers to carbon emissions in the construction industry; for example, Shi et al. [23] used SDA of the input–output model to derive the most significant contribution value of the energy intensity effect to carbon emissions based on Chinese construction industry data from 1995 to 2009. Hong et al. [38] applied SDA to determine the effect of energy growth drivers in China's

Table 1: Various energy parameters.

Energy type	Coal	Coke	Gasoline	Kerosene	Fuel oil	Liquefied petroleum gas	Diesel	Natural gas	Power
Average low-level heat generation	209.08	284.35	430.70	430.70	418.16	501.79	426.52	3,893.1	360.00
Carbon emission factors	26.37	29.42	18.9	19.6	21.1	17.2	20.2	15.32	75.56
Carbon emission factor	0.55	0.84	0.81	0.84	0.88	0.86	0.86	0.60	2.72

Note: The unit of average low-level heat generation is trillion joules/billion kW hr for electricity and trillion joules/billion cubic meters for natural gas; the unit of carbon emission factor is tons of carbon/million kW hr for electricity and tons of carbon/million cubic meters for natural gas.

construction industry from 1990 to 2012. They concluded that increased demand and reduced energy intensity could effectively mitigate carbon emissions [38]. IDA has a relatively low data requirement compared to SDA since national statistical offices can provide the required data. Hence, LMDI factor decomposition in IDA is a more widely used research method in academia to solve carbon emission and energy factor decomposition problems. In this paper, we will analyze the carbon emission influencing factors by combining the characteristics of the construction industry in the Beijing–Tianjin–Hebei regions to establish the following factor decomposition model [39, 40]:

$$C = \sum \frac{E_i}{Q_i} \times \frac{Q_i}{Q} \times \frac{Q}{\mathrm{CGDP}} \times \frac{\mathrm{CGDP}}{\mathrm{GDP}} \times \frac{\mathrm{GDP}}{P} \times P = \sum Y_i S_i \mathrm{FRUP}. \tag{2}$$

E_i denotes the carbon emissions generated by the consumption of the ith energy source, Q_i denotes the consumption of the ith energy source, Q represents total energy consumption, CGDP indicates total construction output, and P means the population. In addition, $I_i = E_i/Q_i$ stands for the ith energy carbon intensity effect, $S_i = Q_i/Q$ indicates the ith energy structure effect, $F = Q/\mathrm{CGDP}$ refers to the energy intensity effect, $R = \mathrm{CGDP}/\mathrm{GDP}$ shows the industrial structure effect, $U = \mathrm{GDP}/P$ indicates the economic impact, and P is the population effect. According to the LMDI additive effect, to further decompose Equation (2), using year 0 as the starting year and year T as the target year, the total change in carbon emissions from 0 to time T in the construction industry in Beijing–Tianjin–Hebei, C, can be expressed as follows:

$$\Delta C = C^{\mathrm{T}} - C^{0} = \Delta C_{\mathrm{Ii}} + \Delta C_{\mathrm{Si}} + \Delta C_{\mathrm{F}} + \Delta C_{\mathrm{R}} + \Delta C_{\mathrm{U}} + \Delta C_{\mathrm{P}}. \tag{3}$$

Decompose the terms on the right side of Equation (3) into the following expressions:

$$\begin{aligned}
\Delta C_{\mathrm{Ii}} &= \sum_i \frac{C_i^t - C_i^0}{\ln C_i^t - \ln C_i^0} \ln \frac{I_i^t}{I_i^0} & \Delta C_{\mathrm{Si}} &= \sum_i \frac{C_i^t - C_i^0}{\ln C_i^t - \ln C_i^0} \ln \frac{S_i^t}{S_i^0}, \\
\Delta C_F &= \sum_i \frac{C_i^t - C_i^0}{\ln C_i^t - \ln C_i^0} \ln \frac{F^t}{F^0} & \Delta C_R &= \sum_i \frac{C_i^t - C_i^0}{\ln C_i^t - \ln C_i^0} \ln \frac{R^t}{R^0}, \\
\Delta C_U &= \sum_i \frac{C_i^t - C_i^0}{\ln C_i^t - \ln C_i^0} \ln \frac{U^t}{U^0} & \Delta C_P &= \sum_i \frac{C_i^t - C_i^0}{\ln C_i^t - \ln C_i^0} \ln \frac{P^t}{P^0}.
\end{aligned} \tag{4}$$

The following formula calculates the contribution of each factor:

$$\begin{aligned}
d_{\mathrm{Ii}} &= \frac{\Delta C_{\mathrm{Ii}}}{\Delta C} d_{\mathrm{Si}} = \frac{\Delta C_{\mathrm{Si}}}{\Delta C} d_F = \frac{\Delta C_F}{\Delta C} d_R = \frac{\Delta C_R}{\Delta C} \\
d_U &= \frac{\Delta C_U}{\Delta C} d_P = \frac{\Delta C_P}{\Delta C}.
\end{aligned} \tag{5}$$

3.2.3. STIRPAT Model. In the 1970s, the American ecologists Ehrlich and Comnoner proposed the IPAT equation mainly to study the effects of population P, affluence A, and technology level T on environmental stress and to establish a constant expression from the relationship of these three factors [41]. However, the IPAT equation, which requires the other two factor variables to remain constant when the one-factor variable is changed, no longer applies to the current complex social environment. To study the influence of multiple variables on the environment, in 1994, Dietz established the STIRPAT model based on the IPAT equation, as this is a stochastic analysis model that overcomes the drawback that the constant expression of IPAT cannot change multiple influencing factors at the same time [42]. The STIRPAT model rejects the assumption of unit elasticity and is stochastic. It can change and extend some of the influencing factors according to the nature and characteristics of the research object. Therefore, it is commonly used to analyze the quantitative relationships of the factors influencing the direct energy consumption carbon emissions in the construction industry and to predict the peak carbon emissions. Its underlying form is as follows [43]:

$$I = aP^bA^cT^de. \tag{6}$$

I, P, A, and T represent carbon emissions, population, wealth, and technological innovation, a denotes the model constant term, and b, c, and d represent the variable elasticity coefficients. If variable A increases or decreases by 1%, carbon emissions will change by $c\%$, and e denotes the error coefficient. To eliminate the unit differences of each influencing factor, both sides of Equation (6) are logarithmically processed to obtain a multivariate linear model.

$$\ln I = \ln a + b\ln P + c\ln A + d\ln T + \ln e. \tag{7}$$

As the construction industry is the pillar industry in the Beijing–Tianjin–Hebei region, I is considered as carbon emission (C), P as population effect, A as economic effect (U), and T as energy intensity effect (F) in the research of carbon emission factors in the construction industry. The energy consumption structure mainly consists of four types of energy: coal, diesel, electricity, and gasoline. The increase in urbanization rate and social progress have stimulated a significant increase in the scale of the construction industry, promoting a continuous increase in carbon emissions in this region. Therefore, in this paper, the two independent variables of diesel energy consumption share (B) and industrial structure (R) in the Beijing–Tianjin–Hebei construction industry are added to the STIRPAT model, and the extended STIRPAT basic model is as follows:

$$\begin{aligned} C &= aP^bU^cF^dB^fR^ge, \\ \ln C &= \ln a + b\ln P + c\ln U + d\ln F + f\ln B + g\ln R + \ln e. \end{aligned} \tag{8}$$

To verify whether economic growth and carbon emissions satisfy the environmental Kuznets hypothesis, GDP per capita is generally introduced to study the relationship between carbon emissions and economic growth. In addition, some scholars have also studied the inverted U-shaped EKC curve of energy intensity and carbon emissions [44, 45]. Therefore, this study adds two other multivariate linear models to explore the EKC effect between GDP per capita and energy intensity in the Beijing–Tianjin–Hebei region, and these are quadratic for affluence and energy intensity to obtain the affluence EKC model and energy intensity EKC model, respectively, as follows [46]:

$$\begin{aligned} \ln C &= \ln a + b\ln P + c(\ln U)^2 + d\ln F + f\ln B + g\ln R + \ln e, \\ \ln C &= \ln a + b\ln P + c\ln U + d(\ln F)^2 + f\ln B + g\ln R + \ln e. \end{aligned} \tag{9}$$

4. Results and Analysis

4.1. Calculation and Analysis of Total Direct Carbon Emissions over the Years. According to Equation (1), we calculate the carbon emissions from the construction industry in Beijing, Tianjin, Hebei, and Beijing–Tianjin–Hebei. As shown in Figure 1, from the partial view, the carbon emissions of the construction industry in Tianjin and Hebei continue to grow, with an average annual growth rate of 6.44% and 10.32% for direct carbon emissions in Hebei and Tianjin, respectively, during the study period. Beijing has always put pollution and carbon reduction at the forefront of the government's efforts, so carbon emissions fluctuate steadily. From 2007 to 2020, the carbon emissions of the construction industry in Beijing–Tianjin–Hebei showed a downward trend, averaging 6.06% per year. The period 2008–2012 saw a significant increase, probably due to the implementation of various economic recovery policies in Beijing–Tianjin–Hebei after the financial crisis, and economic development drove the construction of various infrastructure and housing buildings. In addition, the reason for the growth of carbon emissions is the backward construction technology; most sites are mainly manually operated, resulting in the low economic efficiency of construction enterprises and rough growth in terms of construction energy consumption. From 2012 to 2017, carbon emissions grew slowly because of economic growth, urban village renovation, and continuous urbanization. After 2017, carbon emissions showed a downward trend, and along with the development of industrialization, environmental degradation had a noticeable effect on economic constraints. Construction enterprises developed a circular economy and responded positively to the national "13th Five-Year Plan," which proposed to vigorously promote the application of assembly-type construction, promote the construction of steel structure housing, and reduce construction waste and carbon emissions at construction sites.

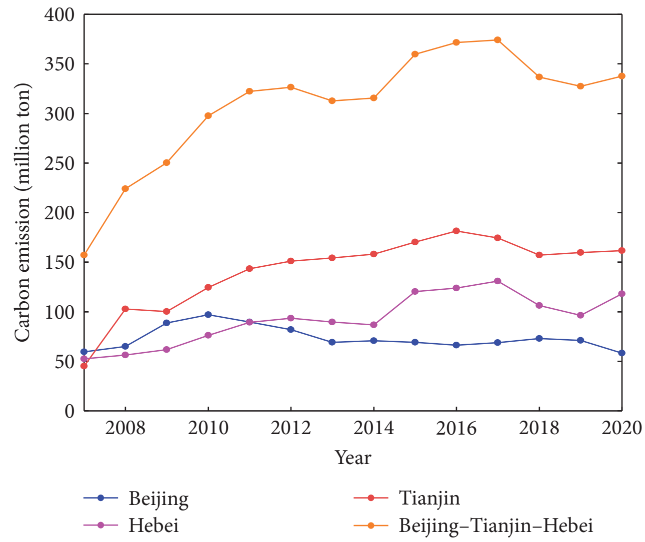

Figure 1: Trend of carbon emissions in the construction industry in Beijing–Tianjin–Hebei from 2007 to 2020.

4.2. Decomposition of Direct Carbon Emission Factors in the Construction Industry. Based on the direct carbon emissions in the Beijing–Tianjin–Hebei region from 2007 to 2020 that were calculated previously, Equations (2)–(6) are used to calculate the carbon emission intensity effect, energy

Table 2: Decomposition results of LMDI in the construction industry in Beijing–Tianjin–Hebei in 2007–2020.

Year	Energy intensity effect ($\triangle C_F$)/104t	Industrial structure effect ($\triangle C_R$)/104t	Energy structure effect ($\triangle C_{Si}$)/104t	Economic effect ($\triangle C_U$)/104t	Population effect ($\triangle C_P$)/104t
2007–2008	19.58	4.32	−6.36	21.43	3.83
2008–2009	−28.25	32.10	0.93	14.71	1.53
2009–2010	−17.71	36.41	−0.16	7.01	9.18
2010–2011	−26.72	5.16	−0.37	35.22	3.25
2011–2012	−27.79	8.06	0.68	20.08	2.85
2012–2013	−40.25	6.67	−1.81	16.90	2.40
2013–2014	−20.47	7.88	−0.84	12.13	2.19
2014–2015	30.47	−10.61	−5.00	12.53	1.14
2015–2016	−8.26	−5.16	−2.82	19.55	1.00
2016–2017	−5.78	−17.41	−1.63	23.00	0.00
2017–2018	−40.21	−9.77	4.87	20.48	−0.29
2018–2019	−23.99	0.47	0.85	15.82	0.45
2019–2020	−6.36	8.42	−0.49	4.99	0.39
Total effect	−195.73	66.53	−12.14	223.86	27.92
Absolute value effect	295.84	152.44	26.81	223.85	28.5

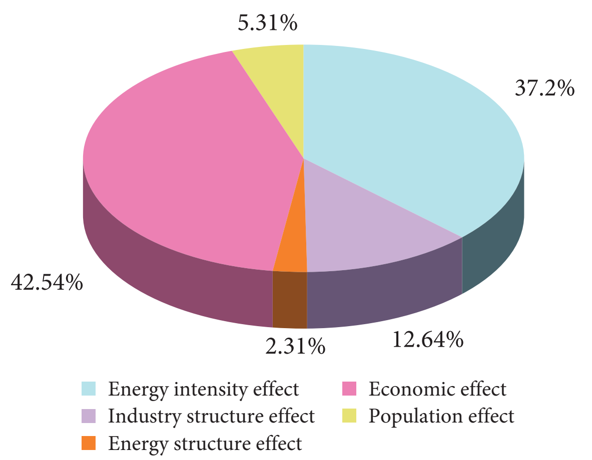

Figure 2: Contribution of direct carbon emission impact factors in the construction industry in Beijing–Tianjin–Hebei in 2007–2020.

structure effect, energy intensity effect, industrial structure effect, economic development effect, and the change in direct carbon emissions in the construction industry caused by the population effect. Because the carbon emission intensity of energy is the carbon emission coefficient, except for electricity, the carbon emission coefficients of other energy sources are fixed constants, causing the carbon emission intensity effect to change very little, so this factor effect is ignored. As shown in Table 2 and Figure 2, among the decomposition effects of the five driving factors affecting the carbon emissions of the construction industry in Beijing–Tianjin–Hebei, energy intensity and energy structure have a reverse inhibitory effect on the direct carbon emissions of the construction industry in Beijing–Tianjin–Hebei; industrial structure, the economy, and population show cumulative effects, and the economic effect has a more obvious promoting effect.

Economic development is the most significant positive factor for direct carbon emissions from the construction industry in Beijing–Tianjin–Hebei. The cumulative contribution of the economic effect in 2007–2020 was $222.86 \times 104t$, with a cumulative contribution of 42.54%. The economic effect values are all positive during the study period because China accounts for nearly half of the new buildings in the world. However, the per capita construction area is only 36 m^2. The future construction volume will continue to increase to meet the demand, leading to increased building energy consumption and a continuous rise in carbon emissions.

Energy intensity is the most significant contributor to suppressing direct carbon emissions, with a cumulative contribution of $-195.73 \times 104t$ and a cumulative contribution of 37.20%, and this has the most considerable absolute effect, indicating that the effect of energy intensity on carbon emissions exceeds that of the industrial structure, energy structure, economy, and population effects. Although energy intensity is crucial in suppressing carbon emissions, it still shows positive values in individual years. In the 2008–2014 "Eleventh Five-Year Plan" period, Beijing–Tianjin–Hebei proposed energy savings as a constraint on economic development in the 5-year development plan, so the contribution rate of 2008–2014 was negative, indicating that Beijing–Tianjin–Hebei was in the "Eleventh Five-Year Plan" and the "Twelfth Five-Year Plan" periods the effectiveness of energy conservation and emission reduction in the construction industry. During the 2015–2020 "13th Five-Year Plan" period, the proposed energy-saving standards for critical parts of the building should be close to international standards, and the proportion of green floor space in new buildings in urban areas should exceed 50%. The efficiency of energy-saving energy use should be improved to achieve sustainable development as soon as possible.

The industrial structure is the second most crucial factor affecting the direct carbon emissions of the Beijing–Tianjin–Hebei construction industry, and the contribution value fluctuation effect is obvious. During 2014–2018, the contribution value of the industrial structure effect is negative, indicating that the Beijing–Tianjin–Hebei region has begun to pay attention to industrial structure adjustment and promote high-end industry development. The National Housing and Urban–Rural Development Conference held in 2014 highlighted the importance of using industrialized building construction methods to improve the competitiveness of construction enterprises and reduce carbon emissions. In 2018–2020, the industrial structure effect rose to a positive value, reminding the construction sector to strengthen innovation in the industry and create new types of enterprises and construction contracting models.

According to the model decomposition results, the population effect is another driver in promoting carbon emissions. The cumulative contribution of the population effect during the study period is 5.31%, and the absolute value effect is $28.5 \times 104t$. The increase in population is 1348.44×104 people, and the increase in carbon emissions is $110.44 \times 104t$. People are producers and consumers. Moreover, an increase in population will lead to employment in the construction industry. The population increases drive economic growth to raise the demand for housing and infrastructure from residents and brings more carbon emissions.

4.3. Analysis and Projection of Direct Carbon Emissions under Different Future Scenarios

4.3.1. Ridge Regression Analysis. This study develops three multiple linear regression models based on the STIRPAT extended model: the basic model, the affluence EKC model, and the energy intensity EKC model. Based on the carbon emissions from the construction industry in Beijing–Tianjin–Hebei from 2007 to 2020 and the yearbook data, a ridge regression analysis in which the advantage is that the fitting effect is more accurate than the least squares method when covariance data are analyzed [47]. If the ridge trace curve tends to be smooth, the penalty coefficient k is introduced, and k is generally in the interval of (0, 1). The size of the k value determines the degree of retention of the original information to obtain more accurate regression coefficient values. As in Figure 3, its regression coefficient of determination decreases when the ridge parameter k grows from 0 to 1. $k = 0.2$ was fitted to the respective variables by providing the ridge regression parameters, as shown in Table 3. Table 3 shows that the F-test is reasonable in the affluence EKC model ($F = 198.20$, $\text{sig} = 0.00$), but the ridge regression parameter for the affluence is +0.02. At the same time, energy intensity is −0.07 in the energy intensity EKC model. Therefore, the Kuznets zone line hypothesis of affluence is not valid for the carbon emissions of the construction industry in Beijing–Tianjin–Hebei from 2007 to 2020. There is a Kuznets curve effect between energy intensity and carbon emissions, so the affluence EKC model is excluded; only the basic model and the energy intensity EKC model and their prediction results are compared and analyzed. The ridge regression analysis of the basic model and the energy intensity EKC model shows that the F-test of the ridge regression models is reasonable (basic model $F = 198.00$, $\text{sig} = 0.00$; energy intensity EKC model $F = 204.06$, $\text{sig} = 0.00$), indicating that the two STIRPAT extended models have good fitting results.

According to the above analysis, the regression coefficients of each factor can be obtained, among which the regression coefficients of the basic model of industrial structure, affluence, diesel energy consumption share, population, and energy intensity EKC model are all positive, indicating a positive influence relationship on total carbon emissions, for which the more significant the regression coefficient is, the stronger the influence is. In the basic model, the regression coefficient of the population is as high as 1.84%, indicating that for every 1% increase in population in Beijing–Tianjin–Hebei, direct carbon emissions increase by 1.84%. In the energy intensity EKC model, the regression coefficient of the population effect is the largest. The regression coefficient of energy intensity is the smallest and is approximately −0.07%, showing that for every 1% increase in energy intensity in Beijing–Tianjin–Hebei, the direct carbon emissions from the construction industry are instead reduced by 0.07%, achieving the effect of energy saving and emission reduction.

4.3.2. Model Accuracy Evaluation. In order to verify the accuracy of the model and overcome the shortcomings of unscientific and inaccurate evaluation of the model accuracy by a single error indicator. In this paper, the grey model (1, 1) and autoregressive integrated moving average models (abbreviated as GM (1, 1), ARIMA) with simple operation and high accuracy are selected to fit the prediction of direct carbon emissions from the construction industry in Beijing–Tianjin–Hebei to avoid the unscientific evaluation of model accuracy by a single error indicator. Four performance indicators, including mean square error (MSE), root mean square error (RMSE), mean absolute error (MAE), and mean absolute percentage error (MAPE), were selected to evaluate the prediction model accuracy, and the calculation formula was as follows [48]:

$$\begin{aligned}
\text{MSE} &= \frac{1}{n}\sum_{i=1}^{n}\left(X_i - \overline{X_i}\right)^2, \\
\text{RMSE} &= \sqrt{\frac{1}{n}\sum_{i=1}^{n}\left(X_i - \overline{X_i}\right)^2}, \\
\text{MAE} &= \frac{1}{n}\sum_{i=1}^{n}\left\|X_i - \overline{X_i}\right\|, \\
\text{MAPE} &= \frac{1}{n}\sum_{i=1}^{n}\left\|\frac{X_i - \overline{X_i}}{X_i}\right\|.
\end{aligned} \tag{10}$$

Table 4 and Figure 4 visualize the prediction performance of the four models. For RMSE, MAPE, MAE, and MSE, the lower the value of the indicators, the higher their prediction accuracy. The energy intensity EKC model has more minor error indicators for each evaluation, followed by the basic model, showing that the prediction accuracy of the energy intensity EKC model is better than that of the basic model. The GM (1, 1) model MAPE is the largest, with a deviation of up to 12% in the prediction, and the ARIMA

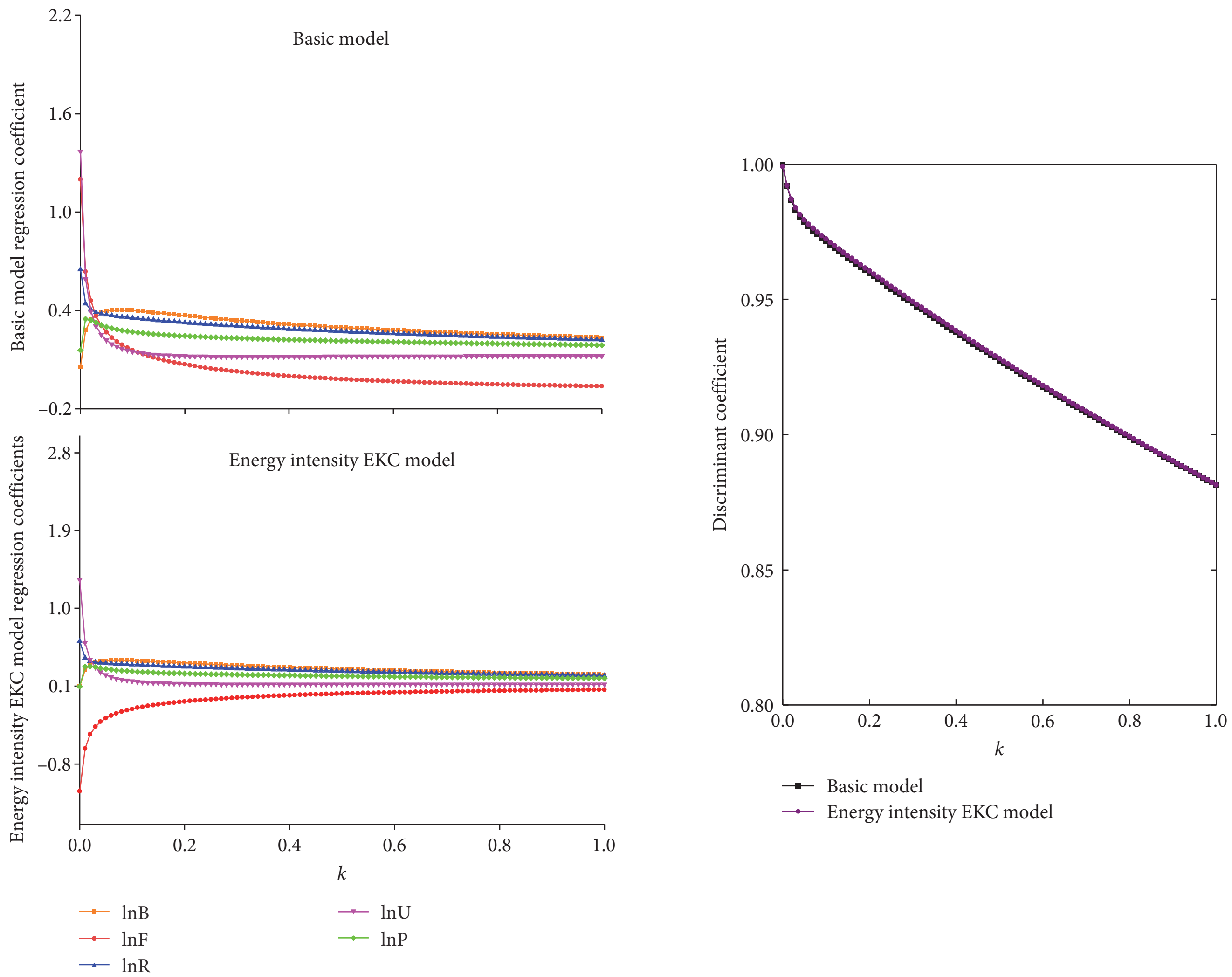

FIGURE 3: Ridge trace plot with discriminant R^2.

TABLE 3: Ridge regression coefficients of the three models.

Variable	Basic model	Affluence EKC model	Energy intensity EKC model
Log of energy intensity ln *F*	0.51	0.51	−0.07
Log of industrial structure ln *R*	0.69	0.71	0.67
Log of affluence ln *U*	0.45	0.02	0.45
Diesel energy consumption share log ln *B*	0.43	0.44	0.45
Log of population ln *P*	1.84	1.85	1.72
Constant term	−13.04	−10.67	−12.95
Corrected discriminant coefficient	0.99	0.99	0.99

EKC, environmental Kuznets curve.

TABLE 4: Comparison of the prediction performance of the four models.

Model	MSE	RMSE	MAE	MAPE
Basic model	41.69	6.46	5.06	0.02
Energy intensity EKC model	41.46	6.44	4.97	0.02
GM (1, 1)	1,550.94	39.38	27.07	0.12
ARIMA	757.36	27.52	23.23	0.08

ARIMA, autoregressive integrated moving average; EKC, environmental Kuznets curve; GM, grey model.

model has a deviation of up to 8%. Therefore, the prediction accuracy of the four models is ranked as follows: energy intensity EKC model > basic model > ARIMA > GM (1, 1).

4.3.3. Scenario Analysis and Parameter Determination. Scenario analysis is a more intuitive qualitative analysis method to develop forecasts for the research object based on the assumption that the development status and trend of the research object can be sustained into the future as the basis

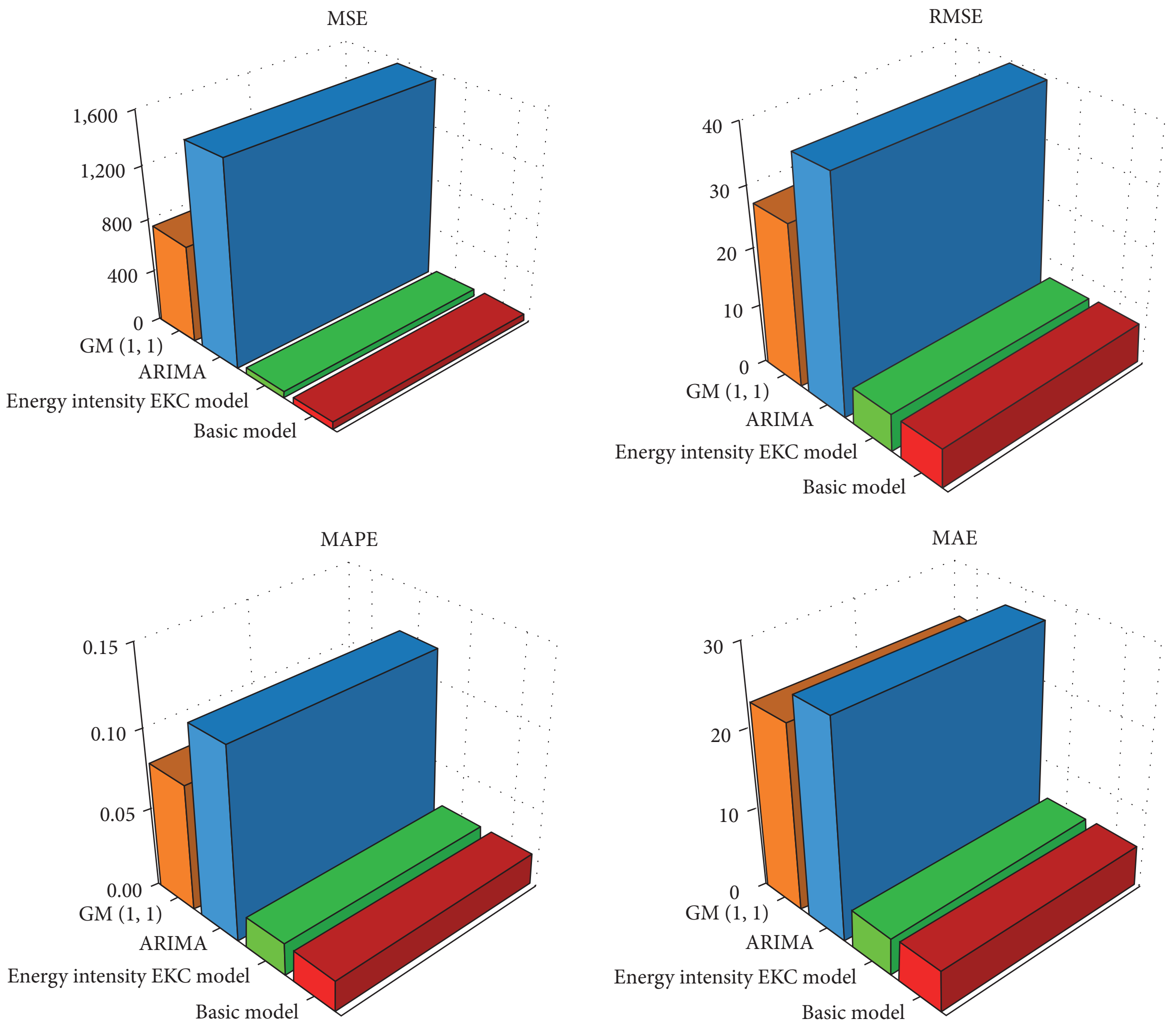

Figure 4: Comparison of error indicators.

for scenario setting [49]. To make the direct carbon emission scenario prediction of the Beijing–Tianjin–Hebei construction industry in 2021–2045 more accurate and reasonable, this research integrates the absolute value magnitude of the regression coefficients of different influencing factors and the decomposition results of LMDI factors. The five influencing factors of population, affluence, diesel energy consumption share, industrial structure, and energy intensity are set up in three models of low, medium, and high, and their setting results are shown in Table 5. The scenario analysis of each influencing factor is as follows.

(1) Population Scale Scenario Analysis. According to the "Decision on Optimizing Fertility Policy for Long-term Balanced Population Development" held by the Central Political Bureau, the "three-child policy" will be liberalized so that the population will grow in the short term. In the "Study on Population Development Strategy of Beijing–Tianjin–Hebei," it is stated that the population of the Beijing–Tianjin–Hebei region will peak at 126 million in approximately 2030, with an annual population growth rate of 1.33%, which is set as the high model growth rate for 2026–2030. However, water shortage and severe water pollution problems in the Beijing–Tianjin–Hebei region lead to a maximum reasonable capacity of 110 million people, setting its growth rate to a low-growth mode. Referring to relevant studies on population projections [50], the Beijing–Tianjin–Hebei region will reach its peak in approximately 2030, after which the average annual growth rate will gradually decrease, and this trend predicts that the population growth rate of Beijing–Tianjin–Hebei from 2021 to 2045 will be 2.21%, 1.01%, 0.11%, −0.59%, and −1.29%.

(2) Energy Intensity Scenario Analysis. Energy intensity is the most significant influencing factor in curbing the effect of carbon emissions. According to the primary goal of economic and social development in the 14th 5-year plan period, the annual average reduction rate of energy consumption per unit of GDP from 2020 to 2025 is 6.63%, and this will be set as the high model. 2016–2020 is the first phase of global implementation of the United Nations 2030 Agenda for Sustainable Development, and the annual decreasing rate of energy intensity from 2016 to 2020 of 6.49% will be set as the medium model. The low mode is the annual decreasing rate of 5.54% from 2010 to 2020. With the promulgation of the technical standard for near-zero energy buildings in 2019, specifying

Table 5: Beijing–Tianjin–Hebei construction industry each influence factor change set.

Changing pattern	Year	Average annual population growth rate (%)	Average annual growth rate of energy intensity (%)	Average annual growth rate of industrial structure (%)	Average annual growth rate of affluence (%)	Diesel energy consumption share (%)
High	2021–2025	2.53	−6.63	3.97	7.47	52.76
	2026–2030	1.33	−7.33	3.47	6.67	49.52
	2031–2035	0.43	−8.03	2.97	6.07	46.48
	2036–2040	−0.27	−8.73	2.47	5.57	43.62
	2041–2045	−0.97	−9.43	1.97	5.07	40.94
Medium	2021–2025	2.21	−6.49	2.77	6.71	51.76
	2026–2030	1.01	−6.79	2.27	5.91	48.58
	2031–2035	0.11	−7.09	1.77	5.31	45.60
	2036–2040	−0.59	−7.39	1.27	4.81	42.79
	2041–2045	−1.29	−7.69	0.77	4.31	40.17
Low	2021–2025	1.16	−5.54	−0.13	5.50	50.76
	2026–2030	−0.04	−5.84	−0.63	4.70	47.64
	2031–2035	−0.94	−6.14	−1.13	4.10	44.71
	2036–2040	−1.64	−6.44	−1.63	3.60	41.97
	2041–2045	−2.34	−6.74	−2.13	3.10	39.39

Table 6: Prediction scenario setting.

Scenario	Diesel energy consumption share	Energy intensity	Industry structure	Affluence	Population
Baseline scenario	Medium	Medium	Medium	Medium	Medium
Rough scenario	High	High	High	High	High
Green development scenario	Low	Low	Low	Low	Low
Energy saving scenario	Low	Low	Medium	High	Medium
Sustainability scenario	Low	Medium	High	High	Medium

the future direction of energy conservation in the building industry, carbon emissions will continue to decline and set a decreasing energy intensity of 0.7% every 5 years for the high mode and 0.3% every 5 years for the medium and low modes according to Wang's research [51].

(3) Industrial Structure Scenario Analysis. In the high mode, due to the coordinated integration strategy of Beijing–Tianjin–Hebei, the construction industry is committed to achieving high speed and high-quality development. Assuming that the scale of the construction industry maintains the growth trend of recent years after 2020, the average growth rate of 2015–2020 is 2.77%, and this is set as the average annual growth rate of the industrial structure under the high mode. With the upgrading of the industrial structure and reducing the reliance on the construction industry, the average annual growth rate from 2007 to 2020 will be the growth rate of the industrial structure in the medium mode and the decreasing rate of 0.5% every 5 years in the high, medium and low modes.

(4) Affluence Scenario Analysis. According to the comparison of developed countries and similar regions, GDP per capita growth tends to flatten as the economy develops. The 2015–2020 GDP per capita annual growth rate is 7.47% and is set as the high mode GDP per capita growth rate in 2021–2025. Based on the "Beijing–Tianjin–Hebei Cooperative Development Plan" and the "14th Five-Year Plan" of Beijing–Tianjin–Hebei, the GDP per capita growth rate of Beijing–Tianjin–Hebei from 2021 to 2025 is calculated as 6.71% and is set as the low model scenario value, and the GDP per capita is reduced by 0.8%, 0.6%, 0.5%, and 0.5% in each phase.

(5) Analysis of Diesel Consumption Scenarios. In recent years, as China's economic development entered a new normal during the 13th 5-Year Plan period, diesel consumption per unit of GDP in the construction industry has declined yearly. According to the document "Energy Production and Consumption Revolution Strategy," the energy consumption in 2030 will not exceed 6 billion tons of standard coal, the proportion of diesel energy consumption will drop to 47.64%, and in 2025, the proportion will drop to 50.76%.

Based on the shadow of the low, medium, and high change patterns of each influencing factor in the construction industry in Beijing–Tianjin–Hebei from 2021 to 2045, five scenarios are set in this paper, as shown in Table 6: baseline scenario, crude scenario, green development scenario, energy saving scenario, and sustainable development scenario.

Under the base scenario, the changes in the impact factors of the construction industry in Beijing–Tianjin–Hebei are all medium values. This indicates that under this scenario assumption, the construction industry will have stable and good development momentum with economic and social progress under the economic and social development objectives in the 14th

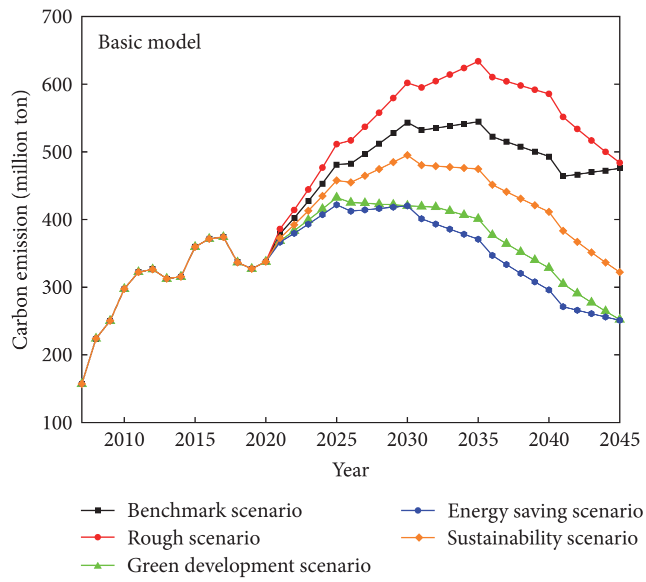

FIGURE 5: Projected direct carbon emissions from the construction industry in Beijing–Tianjin–Hebei.

TABLE 7: Projections of direct carbon attainment in the construction industry in Beijing–Tianjin–Hebei under different scenarios.

Scenario	Basic model		Energy intensity EKC model	
	Time of peak carbon emission (year)	Peak carbon emission (104*t*)	Time of peak carbon emission (year)	Peak carbon emission (104*t*)
Baseline scenario	2035	544.46	2035	442.15
Rough scenario	2035	633.82	2035	450.97
Green development scenario	2030	432.47	2030	376.24
Energy saving scenario	2028	421.74	2028	366.81
Sustainability scenario	2030	495.10	2030	414.60

EKC, environmental Kuznets curve.

5-Year Plan period. The change of all influence factors in the crude scenario is in high mode, indicating that the Beijing–Tianjin–Hebei region that pursues construction economic growth and pays less attention to environmental changes, is a relatively crude way of economic development. In the green development scenario, this region attaches importance to the green development of the construction industry. It fully considers the future economic, social, and environmental development needs, and the influence factors are in low mode. The energy efficiency scenario slows down the social development trend. It places more emphasis on environmental protection compared to the baseline scenario, so low values are chosen for the share of diesel energy consumption and energy intensity. The sustainable development scenario is to maximize the net benefits of the construction industry while maintaining a well-developed environmental system and to achieve sustainable development by considering environmental protection while developing the economy.

4.3.4. Prediction Results and Analysis. According to the constructed basic model and energy intensity EKC model, the direct carbon emissions from the construction industry in Beijing–Tianjin–Hebei are predicted for 2021–2045, and the prediction results are shown in Figure 5. The peak size and year of carbon attainment under different design scenarios are shown in Table 7, and the average cumulative carbon emission reduction ratio over the prediction period under different scenarios is further calculated as shown in Table 8.

TABLE 8: Decrease ratio of average cumulative direct carbon emissions in the projection period under different scenarios compared to the baseline scenario.

Scenario	Basic model (%)	Energy intensity EKC model (%)
Baseline scenario	–	–
Rough scenario	5.65	1.25
Green development scenario	−4.27	−6.03
Energy saving scenario	−10.11	−10.82
Sustainability scenario	−10.59	−10.37

EKC, environmental Kuznets curve.

From the above prediction results, it can be seen that the prediction curves of carbon emissions of the basic model and the energy intensity EKC model under five scenarios have similar trends, and the peak carbon emission time is the same. The comparison of the two models shows the accuracy and scientificity of the prediction results.

Under the baseline scenario, the raw and energy intensity EKC models reach the carbon peak in 2035. The peak carbon peak values are $544.46 \times 104t$ and $422.15 \times 104t$, respectively, and these cannot achieve the target carbon peak in 2030. This indicates that if the government does not adjust the original emission reduction measures and economic dynamics, the direct carbon emissions from the construction industry in Beijing–Tianjin–Hebei will increase significantly, reminding the government to adopt more effective energy-saving approaches based on the existing policies. Compared with the baseline scenario, the average cumulative carbon emission ratio increases to 5.65% and 1.25% during the forecast period of the crude scenario, warning that if this region pursues economic growth unilaterally and neglects environmental protection, it will be challenging to achieve the goal of carbon neutrality. Under the green development scenario, the average cumulative carbon emission reduction rate of the Beijing–Tianjin–Hebei construction industry is approximately 5.15%, and this is undesirable because the economic level is developing in a low mode. However, the carbon peak is reached within the specified years. Under the energy-saving scenario, the Beijing–Tianjin–Hebei construction industry develops rapidly economically. It reaches the carbon peak in 2028 with peak carbon values of $421.74 \times 104t$ and $366.81 \times 104t$, as well as an average cumulative carbon emissions decrease ratio of approximately 10.47% compared with the baseline scenario, reaching the carbon peak time target in advance and significantly reducing carbon emissions. This shows that diesel energy consumption reduces the proportion of the average annual growth rate of energy intensity by 5.54% to ensure a high economic growth model while the carbon peak has advanced. Under the prospect of sustainable development, 2030 is still the time of carbon peaking in the Beijing–Tianjin–Hebei construction industry, with a peak carbon emission of approximately $454.85 \times 104t$ and slightly higher carbon emission per unit GDP. However, carbon emissions continue to decline after peaking and are expected to achieve carbon neutrality in 2060.

The above analysis shows that the optimal emission reduction scenario for the Beijing–Tianjin–Hebei construction industry is the energy-saving scenario, and this not only has the earliest peak time and the lowest peak but can also take into account the development of the economic level while saving energy and reducing emissions, and thus is in line with the development goals of the 14th 5-year plan of Beijing–Tianjin–Hebei.

5. Conclusions and Recommendations

This paper uses the LMDI factor decomposition method to analyze the effects of five drivers on carbon emissions in the construction industry in Beijing–Tianjin–Hebei from 2007 to 2020: energy structure, energy intensity, industrial structure, affluence, and population. The STIRPAT model after ridge regression analysis is used to forecast carbon emissions in the construction industry for five different scenarios, with the following conclusions:

(1) The LMDI factor decomposition is used to decompose the change in direct carbon emissions of the construction industry in Beijing–Tianjin–Hebei in 2007–2020 into five factors: energy intensity, industrial structure, energy structure, economy, and population. Among them, energy intensity and energy structure can suppress carbon emissions in the construction industry, and energy intensity has a continuous significant carbon suppression effect. During the sample period, industrial structure, economy, and population positively contributed to carbon emissions in the construction industry during the sample period, where the economy has the most significant contribution to carbon emissions in Beijing–Tianjin–Hebei, followed by energy intensity and the minor energy structure.

(2) Based on the decomposition results and national policy planning, five direct carbon emission projection scenarios for the construction industry in Beijing–Tianjin–Hebei are set. Among them, only the energy conservation and emission reduction scenario, the basic model, and the energy intensity EKC model predict that carbon peaks in 2028 and the average cumulative carbon emissions decrease at a relatively large rate compared with the baseline scenario. This is consistent with China's strategic goal of reaching a carbon peak in 2030 and carbon neutrality in 2060.

(3) The average cumulative carbon emissions of the basic model and energy intensity EKC model for the forecast period in the region are approximately 3.45%, −5.15%, −10.47%, and −10.48% compared to the baseline scenario. The energy saving and emission reduction scenarios for Beijing–Tianjin–Hebei, without affecting economic development and population growth, reducing the share of diesel energy consumption and energy intensity, and further adjusting the energy structure by strongly advocating the use of clean energy, will be the most effective measures for carbon emission reduction.

Based on the results of the above analysis, the following recommendations are provided for the actual situation of the construction industry in the Beijing–Tianjin–Hebei region:

(1) Adjust the energy mix to reduce the share of diesel energy consumption. When pricing energy sources such as diesel, gasoline, natural gas, and electricity, raise the price of diesel energy, lower the price of clean energy sources such as natural gas and electricity, and provide financial subsidies and lower taxes to construction companies that use clean energy.

(2) Encourage green building technology innovation to reduce energy intensity. The primary way to fundamentally reduce carbon emissions and effectively use energy is to reduce energy intensity through technological innovation, improved energy efficiency, and building energy efficiency technologies. Promote building energy efficiency technologies and strengthen research

on green building technologies and materials. For example, increase funding for research and development of renewable energy, new wall materials and wall insulation materials, and research and development of green building materials with low carbon emissions as raw materials. Local governments should strongly support the research of the green industry and carry out green building materials industry base with typical engineering projects and areas as the pilot. Encourage research on zero-carbon buildings, community technology systems, and critical technologies, support research on zero-carbon building environment and energy consumption post-assessment technology, and develop zero-carbon communities.

In this paper, when studying carbon emissions in the construction industry, only the influence of direct factors of carbon emissions in the construction industry is considered, and the study of indirect carbon emissions of construction materials and whole life cycle carbon emissions in the construction industry is lacking. Meanwhile, due to data availability, the most influential factors are selected as macroindicators, such as CGDP and total energy consumption. Future studies should include indicators of different construction methods and construction processes. Despite these challenges, the five scenarios set in this paper can provide a reference for setting other new scenarios to help achieve the commitment of carbon peaking in 2030 and carbon neutrality in 2060 for the construction industry and enable policy-makers, engineers, and building users to make more rational decisions on the future of construction for economic and social sustainability.

Data Availability

The data used to support the findings of this work are included in the article.

Conflicts of Interest

The author declares that there are no conflicts of interest.

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