Carbon emissions index decomposition and carbon emissions prediction in Xinjiang from the perspective of population-related factors, based on the combination of STIRPAT model and neural network

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Abstract
In the present study, the STIRPAT model was adopted to examine the impacts of several factors on dioxide emissions using the time series data from 2000 to 2019 in Xinjiang. The said factors included population aging, urbanization, household size, per capita GDP, number of vehicles, per capita mutton consumption, education level, and household direct energy consumption structure. Findings were made that the positive effects of urbanization, per capita GDP, per capita mutton consumption and education on carbon emissions were obvious; the number of vehicles had the biggest positive impact on carbon dioxide emissions; and household size and household direct energy consumption structure had a significantly negative impact on carbon emissions. Based on the aforementioned findings, the GA-BP neural network was introduced to predict the carbon emission trend of Xinjiang in 2020–2050. The results reveal that the peak time of the low-carbon scenario was the earliest, between 2029 and 2033. The peak time of the middle scenario was later than low-carbon scenario, between 2032 and 2037, while the peak time of the high-carbon scenario was the latest and was unlikely to reach the peak before 2050.

Keywords Carbon emissions prediction · Index decomposition · STIRPAT model · GA-BP neural network

Introduction
Climate change has become an important topic of discussion around the world. In recent years, with the rapid growth of China’s economy, the contradiction between population and environment has become more prominent. At present, China has become the country with the largest carbon emissions in the world (Cai et al. 2019). China’s carbon emissions will peak by 2030. And China has pledged to strive to be carbon neutral by 2060. As the world’s most populous country, China’s carbon emissions are inextricably linked to its population-related factors. In some developed countries, the household sector already contributes more to carbon emissions than the industrial sector (Wang et al. 2017b). Population growth leads to an increase in carbon emissions (Guan et al. 2008; Xu et al. 2014), but in the long run, it may have reduced carbon emissions per person. China’s rapid urbanization has led to rapid growth in urban housing and transportation demand, leading to more energy consumption and carbon dioxide. But the results were not consistent across regions and groups. On top of that, there is still a lot of uncertainty about the impact of demographic factors, such as aging, education, wealth, and ethnic culture, on carbon emissions and to what extent. Therefore, the impact of population-related factors on carbon emissions is worth studying and exploring.

China has a large number of provinces, among which there are huge differences in economic and demographic...
factors. When achieving carbon peak and carbon neutral path, we cannot only start from the national scale. It is necessary to carry out provincial research according to the reality of different provinces. Xinjiang is a major energy province in China. It possesses not only a large amount of fossil energy such as oil and natural gas, but also abundant renewable energy such as wind and solar energy (Fan et al. 2017). By the end of 2019, Xinjiang had 25.2322 million permanent residents, ranking only 24th in China. Xinjiang’s GDP was 1359.711 billion yuan in 2019, ranking only 25th in China. However, Xinjiang’s per capita energy consumption is among the highest in China, surpassing the populous and economically powerful provinces such as Henan, Shandong, and Guangdong (Ding 2017). Due to its low economic level, Xinjiang has a big gap with eastern provinces in terms of education and wealth. Xinjiang also has its unique geographical location and ethnic culture, which results in its energy consumption structure and trend being greatly different from other provinces. Therefore, it is necessary to study the impact of population-related factors on carbon emissions in Xinjiang.

**Literature review**

**Review on the impact of population-related factors on carbon emissions**

Many scholars have studied the impact of population-related factors on carbon emissions. Population size is one of the important components of research content and also the main factor affecting carbon emission (Dong et al. 2018b; Li et al. 2019; Nejat et al. 2015; Regmi and Rehman 2021; Wang et al. 2017a; Zeqiong et al. 2020). However, according to the research results of some small- and medium-sized regions, in a long-time scale, population size has little impact on carbon emissions, or even a negative factor (Alam et al. 2016; Chai et al. 2021; Guan et al. 2008). Urbanization and rural-to-urban migration do not necessarily increase carbon emissions for different countries, regions, or even provinces and cities within the same country. Many scholars have found that the development of urbanization and the long-term rural-urban migration obviously increases the carbon emissions of residents (Fan et al. 2019; Wang et al. 2019b). But some scholars come to a different conclusion. Wei et al. (2014) argued that there was not enough evidence to show that the direct carbon emissions of residents moving to Shanghai from rural areas increased. Ala-Mantila et al. (2014) and Rehman et al. (2021) found that urban population has less carbon emissions than rural. Li et al. (2015) and Fan and Fang (2020) showed that urbanization contributes to carbon emissions from residents’ direct consumption, but the contribution is very small.

Aging population and educational levels are also factors in carbon emissions. Yang et al. (2015) and Wen and Zhang (2020) showed that the change of population age structure in Beijing had a significant positive impact on carbon emissions, and the continuous expansion of aging population would continue to increase environmental pressure. Liddle and Lung (2010) found that people over 65 years old in developed countries had a positive impact on residential energy consumption. Zhang and Tan (2016) found that in general, the proportion of elderly people was positively correlated with carbon emissions in China, but there were regional differences in the impact of population aging on carbon emissions. Aging population has increased emissions in eastern China while reducing emissions in central and western China (Wang et al. 2017b). Yang and Wang (2020) conducted an empirical analysis of the nonlinear relationship between population aging and carbon emissions in 10 provinces in China and found that population aging has a negative coefficient on carbon emissions. The panel threshold regression analysis of 137 countries by Wang and Wang (2021) found that with the increase of the degree of population aging, there is a positive correlation between the high-income group and carbon emissions, and a negative correlation between the middle-income group and carbon emissions. Some scholars believe that well-educated residents are more likely to respond to low-carbon behavior and consume energy conservatively. Therefore, education is an effective way to reduce household energy consumption (Liu et al. 2014) (Ye et al. 2017) (Chen and Li 2019). However, generally speaking, high education means higher income and stronger spending power. Mi et al. (2018) found that people with higher education generally have higher carbon consumption behaviors. But in terms of electricity consumption, education makes little difference (Cui et al. 2019).

In addition, some scholars have done some research on the impact of household size on carbon emissions. In Ireland, single-person and two-person households are the highest carbon emitters (Kenny and Gray 2009). Minx et al. (2011) believed that the impact of household size on carbon emissions in China in the future would be less significant than other population-related factors. Liddle (2013) concluded that the average household size was negatively correlated with the total carbon emission. Yang et al. (2020) found that the decline of rural household size in Guangdong Province was a major contributor to the decoupling of carbon emissions.

**Review on the carbon emission forecast**

China has pledged to peak its carbon emissions by 2030 and achieves carbon neutral by 2060. Therefore, scholars began to pay close attention to the issues related to carbon emission forecasting. The research areas, methods, and regions are
also different. From the perspective of research direction, some scholars focus on industry carbon emission prediction. Hirvonen et al. (2019), Langevin et al. (2019), and Huo et al. (2021b) mainly studied the carbon emission prediction of residential construction industry, and believed that the peak time of carbon emission is before 2050, and the latest time is generally around 2040. Breyer et al. (2019) and Khanna et al. (2021) mainly focus on forecasting research on transport carbon emissions, which will be reduced by more than 50% by 2050. Carbon emission prediction and carbon emission reduction path research of industrial sectors have also received extensive attention. In addition to the research on the overall industry (Wang et al. 2019a), they also include cement industry (Wei and Cen 2019), steel industry (Ryan et al. 2020), aluminum industry (Yu et al. 2021), and power industry (Yu et al. 2020).

For carbon emission prediction methods, scholars mainly adopt top-down IPAT and STIRPAT models (Sun et al. 2019; Zuo et al. 2020), CGE model (Thepkhun et al. 2013; Zou et al. 2018), and the EKC t model Le and Ozturk (2020). Jiang et al. (2019) and Shimoda et al. (2021) studied the carbon emission forecast of China and Japan, respectively, and the results show that China’s carbon dioxide emission from energy consumption will be reduced by 66% by 2050, while Japan may achieve net zero emission by 2050. Some scholars have also introduced machine learning methods to predict carbon emissions. Mardani et al. (2020) used self-organizing mapping clustering algorithm, adaptive neural fuzzy reasoning system, and artificial neural network to predict carbon dioxide emissions. The results showed that the average error of prediction results was very small, and the accuracy of the results was much higher than that of the single multi-linear regression model. Magazzino et al. (2021) constructed a machine learning model to predict the causal relationship between solar and wind energy production, coal consumption, economic growth, and CO₂ emissions and found that carbon emissions would decrease in the USA and increase in India.

In terms of research regions, most of the studies are focused on the national scale (Huo et al. 2021a; Mirzaei and Bekri 2017; Olkkonen et al. 2021); some scholars have also carried out studies on provincial scale (Wei et al. 2018) and city scale (Ouria and de Almeida 2021; Wang et al. 2020). From a macro point of view, research on national scale is necessary, but the implementation of low-carbon policies should be carried out according to local characteristics. Therefore, the study of provinces is necessary.

To summarize, there are few studies on carbon emission prediction from the perspective of population. As a national autonomous region, Xinjiang has its own characteristics in educational concepts and residential behaviors. And almost the population-related factors on the impact of Xinjiang residents carbon emissions related research. Under the background of carbon peak in 2030 and carbon neutral in 2060, we will achieve carbon emission reduction on the basis of social stability and development. It is important to study the impact of population-related factors on carbon emissions in Xinjiang. This study also provides reference for local government policy formulation and implementation.

**Method**

**Research area**

Xinjiang, located in northwest China, is the largest provincial administrative region in China, accounting for one-sixth of China’s total land area. Xinjiang is located between 75°–95° east longitude and 35°–50° north latitude. The study area is shown in Fig. 1.

**Decomposition methodology**

The STIRPAT model is one of the classical methods to study the factors affecting carbon emissions. Many scholars use this method to study the impact of time series data on carbon emissions (Huo et al. 2020; Wang et al. 2017b; Zhou and Liu 2016). In this paper, STIRPAT model is used to decompose the population-related factors of carbon emissions in Xinjiang.

In the 1970s, Eheilich and Holden proposed the IPAT model (Holdren and Ehrlich 1974). The relevant equation is as follows:

\[ I = P \times A \times T \]  

(1)

In the model, \( I \) represents environmental pressure, \( P \) is population-related factor, \( A \) is affluence factor, and \( T \) is technology factor. The IPAT model is a conceptual description that is only suitable for qualitative research. The application of this model has some limitations. As the content of the research becomes more and more complex, its disadvantages gradually appear.

In order to overcome the limitations of the study, Dietz and Rosa proposed STIRPAT stochastic model based on the extension of IPAT model (Dietz and Rosa 1994). The relevant equation is as follows:

\[ I = \beta P^a A^b T^c \mu \]  

(2)

where \( \beta \) is the model parameter, \( a, b, \) and \( c \) are the exponential terms of population factor, affluences, and technology, and \( \mu \) is the error term. The STIRPAT model has strong flexibility and can be extended according to the research content. It has been used to analyze the influencing factors of energy consumption and CO₂ emission.
After logarithmic processing of Eq. (2) and (3) is obtained:

\[
\ln I = \ln \beta + a \ln P + b \ln A + c \ln T + \ln \mu
\]  

(3)

Take \(\ln I\) as the dependent variable and \(\ln P, \ln A, \) and \(\ln T\) as the independent variables, \(\ln \beta\) as the constant term, and \(\ln \mu\) as the error term. According to the concept of elastic coefficient, when other influencing factors remain unchanged, every 1% change of driving force influencing factors \((P, A, T)\) will cause a% \((b\%, c\%)\) change of \(I\), respectively.

This paper takes population-related factors as the research content, so new definitions are added to variables in the model. All variables are selected around demographic factors. The extended model is as follows:

\[
\ln I = \ln \beta + a \ln PP_i + b \ln PA_i + c \ln PT_i + \ln \mu
\]  

(4)

where \(PP_i\) represents for physical population factors, \(PA_i\) stands for affluent population factors, and \(PT_i\) is for technological population factors, \(\ln \mu\) as the error term, \(I\) is the detailed index, which is shown in the following Table 1:

Based on the extension of STIRPAT model, the above 8 indicators are brought into the model. The specific model equation is as follows:

\[
\ln I = \ln \beta + a_1 \ln PP_1 + a_2 \ln PP_2 + a_3 \ln PP_3 + b_1 \ln PA_1 + b_2 \ln PA_2 + b_3 \ln PA_3 + c_1 \ln PT_1 + c_2 \ln PT_2 + \ln \mu
\]  

(5)

where \(\ln \beta\) is the constant term and \(\ln \mu\) is the error term. The left side of the equation is the dependent variable, and the right side is the independent variable. \(a_i, b_i,\) and \(c_i\) are elastic coefficients.

**Data sources and indicators interpretation**

**Data source**

The main content of this paper is to discuss the impact of population-related factors on carbon emissions in Xinjiang, so the carbon emissions of Xinjiang are not calculated by ourselves, and the carbon emissions data used are from the research of other scholars. Xinjiang’s carbon emissions data download in Carbon Emission Accounts and Datasets...
The direct energy consumption data of Xinjiang residents comes from the \textit{Energy Balance Sheet of Xinjiang Uygur Autonomous Region in The China Energy Statistical Yearbook (2000–2019)}. The primary energy consumed by Xinjiang residents includes raw coal, coke oven gas, natural gas, kerosene, gasoline, diesel oil, and liquefied petroleum gas. Data on urbanization, number of vehicles, per capita GDP, and per capita mutton consumption are from \textit{Xinjiang Statistical Yearbook (2000–2019)}. Data on aging, household size, and education level were obtained from \textit{China Statistical Yearbook (2000–2019)}.

### Indicator interpretation

Indicators selection basis and interpretation are as follows:

1. Urbanization is a classic indicator. The overall level of urbanization in Xinjiang is still relatively low. By 2019, the urbanization rate in Xinjiang was 51.87%. The main reason for selecting the aging index is that the energy consumption concept of the elderly is quite different from that of the middle and young people. In general, older people tend to be conservative in their energy consumption. However, in terms of travel, medical care, and other aspects, the elderly consumes more than the normal middle-aged and young people, which indirectly increases carbon emissions. Xinjiang, as an ethnic minority region, may have unexpected differences. Households in Xinjiang are generally larger than those in other Chinese provinces, and each household has guaranteed basic expenditures such as heating, cooling, basic appliances, and transportation, all of which add to direct and indirect household carbon emissions. But in Xinjiang, one aspect to consider is that it has long, cold winters and very high-energy consumption due to heating (about 6 months);

2. Per capita GDP, number of cars, and per capita mutton consumption are used for research in this paper. Generally speaking, per capita GDP is a measure of people’s economic level. In the phase of rapid development, regions with high per capita GDP have high-energy consumption and therefore high per capita carbon emissions. When economic development reaches a certain level and the economy is transformed into a green development model, the higher per capita GDP is, the lower per capita carbon emissions will be. The number of cars is a good measure of how wealthy Xinjiang residents are. For the poor, cheap bikes and public transport are the mainstay. The average level of residents, generally in a family unit, will buy a car to meet daily travel needs. Wealthy people own more than one car. Due to tradition and custom, mutton is the essential meat for Xinjiang residents. Xinjiang people’s meat is mainly mutton, Xinjiang meat consumption, mutton more than 40% (Yin et al. 2020). While Xinjiang’s per capita consumption of mutton has fallen, one side of the story is that prosperity is on the rise. Because beef and seafood are more expensive than mutton;

3. The education level of residents is very important for carbon emissions. Highly educated people, who are mostly middle class, are likely to consume more energy (Xu et al. 2015). However, people with higher education have more potential to adopt low-carbon life concepts and practice low-carbon lifestyles. The energy structure of residents’ direct consumption can explain the dependence of the region on coal to some extent. At present, Xinjiang residents’ direct energy consumption is still dominated by coal, and the contributors are mainly rural residents. Xinjiang is rich in natural gas, solar energy, and wind energy, so it has great potential to change the direct energy consumption structure of residents.

| Indicators Descriptions | Units |
|--------------------------|-------|
| Carbon emissions (I)     | Mt    |
| Aging (PP1)              | %     |
| Urbanization (PP2)       | %     |
| Household size (PP3)     | units |
| Per capita GDP (PA1)     | $     |
| Number of vehicles (PA2) | Units |
| Per capita mutton consumption (PA3) | kg |
| Education level (PT1)    | %     |
| Household direct consumption of energy structure (PT2) | % |
Analysis of regression results

**Multicollinearity analysis** Through the correlation test of all variables, it can be seen from Fig. 2 that there is a high correlation between most variables. Therefore, it can be determined that there is a high correlation between variables. To determine whether multicollinearity exists between dependent variable I and independent variables PP₁, PP₂, PP₃, PA₁, PA₂, PA₃, PT₁, and PT₂, a multicollinearity test is performed for each variable. The intensity of collinearity is determined by evaluating its variance inflation factor (VIF). VIF is the most commonly used measurement method of independent variable multicollinearity in regression models. In general, if VIF is greater than 10, it is collinearity (Wang et al. 2013; Wang et al. 2012). Table 2 shows OLS results. Except PP₁, PP₃, PA₁ and PA₂, the VIF is all greater than 10, indicating severe collinearity. Therefore, the reliability of regression coefficient in Table 2 is low, and the size of influencing factors should be discussed after collinearity is eliminated.

**Ridge regression results** In order to ensure the validity and accuracy of the regression model, overcome the influence of multicollinearity among variables on the regression results, and improve the stability and reliability of the regression coefficient, ridge regression method was used to estimate the regression model (Shahbaz et al. 2016). Ridge regression is one of the most effective solutions for model estimation and regression coefficient reliability because it can significantly reduce the large standard error between the related independent variables. Ridge regression estimation based on formula (4) is used, and K is 0.27 to select ridge regression coefficient, as shown in Table 3.

According to the regression results in Table 3, among the population-related factors affecting carbon emissions in Xinjiang, lnPA₁ (numbers of vehicle) has the largest positive impact, followed by lnPP₁ (urbanization), lnPP₃ (per capita GDP), lnPA₃ (education level), and lnPA₂ (per capita mutton consumption), and lnPP₁ (aging) has the smallest positive impact. The lnPP₂ (household size) and the lnPT₁ (household direct energy consumption) structure have an important negative impact on carbon emissions.

Since the beginning of this century, Xinjiang’s economic development has become a top priority. With the rapid

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**Table 2** OLS results

| Indicators | Unnormalized coefficient | t    | Sig  | VIF  |
|------------|--------------------------|------|------|------|
| lnI        | 1.685                    | 0.748| 0.474|      |
| lnPP₁      | 0.463                    | 0.403| 0.696| 140.905 |
| lnPP₂      | −0.096                   | −0.374| 0.717| 2.673 |
| lnPP₃      | 0.12                     | 1.229| 0.25 | 10.33 |
| lnPA₁      | 0.292                    | 0.912| 0.385| 248.345 |
| lnPA₂      | 0.169                    | 4.795| 0.001| 18.7 |
| lnPA₃      | 0.074                    | 0.421| 0.684| 4.251 |
| lnPT₁      | −0.759                   | −1.118| 0.292| 9.841 |
| lnPT₂      | −0.235                   | −1.807| 0.104| 7.034 |

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Fig. 2 Correlation thermodynamic diagram of each index
economic development of Xinjiang, the per capita GDP has greatly increased, and residents’ demand for vehicles and purchasing ability has also significantly increased, so the urbanization of the number of cars and per capita GDP have a great impact on the growth of carbon emissions. Xinjiang’s urbanization level increased from 35.21% in 2000 to 50.91% in 2019, with a fast growth rate. Its positive impact on carbon emissions is second only to the number of vehicles and higher than per capita GDP. This is mainly due to China’s “Western Development” strategy. But rapid urbanization is also closely linked to Xinjiang’s natural environment. Xinjiang is located in arid area, precipitation is scarce, and desertification is serious. Many villages are in remote locations, with poor natural conditions and inconvenient transportation. As a result, a considerable number of rural residents migrate to cities to survive. Education level has a positive impact on carbon emissions, indicating that the highly educated people in Xinjiang are still in the stage of high-carbon emissions. Generally speaking, the income of the people with higher education is richer than that of the people with lower education, and the consumption power is stronger than that of the people with lower education. In Xinjiang, there are two difficulties for well-educated people to adopt a low-carbon lifestyle. Firstly, the overall economic level of Xinjiang is still low, and the main task is still to develop the economy. Secondly, there are few low-carbon products available in Xinjiang. Currently, the increase in per capita mutton consumption in Xinjiang is mainly contributed by rural residents. After the income level increases, urban residents’ craving for food is diversified. In other words, urban residents have little room for improvement in their demand for mutton, so they tend to buy more expensive food such as seafood and beef rather than eat more mutton. But in rural areas, food diversity is not as high as in urban areas, plus meat consumption is not as high as in urban areas. So rural residents, with higher incomes, can buy more mutton to meet their protein needs. This proves that per capita mutton consumption indirectly represents an increase in carbon emissions. At the affluent level, the pension of the elderly is generally lower than the working wage, and the elderly without pension can only engage in some low-intensity and low-paid jobs due to physical strength and energy. Therefore, in terms of consumption ability and consumption desire, the elderly are not as good as the young. In terms of concept, the consumption of the elderly is conservative compared with the young; the elderly is more “energy saving and emission reduction”. In both ways, aging has a negative effect on carbon emissions. However, the regression results in this paper show that aging is a positive index of carbon emissions, although the impact is small. It is possible that medical and healthcare services for the elderly have contributed to the increase in carbon emissions in Xinjiang. Household size has a strong negative impact on carbon emissions, indicating that small households are more “low-carbon”. The reasons may lie in the following: first, the aging of the population and the acceleration of urbanization process leads to the increasing number of empty-nest families, especially in rural areas. Secondly, influenced by the family planning policy, a large number of young people marry and have children at a later age. The negative impact of household direct energy consumption structure on carbon emission is mainly due to the change of regional household energy policy. The energy change path of domestic open fire consumption is raw coal—liquefied petroleum gas—natural gas and that of heating consumption is raw coal, natural gas.

**Carbon emission prediction**

**Prediction methods**

**BP neural network**

In 1986, Rumelhart and Mecelland proposed the error back propagation learning algorithm of multi-layer network, known as BP algorithm. At present, BP algorithm has developed into the most important and widely used artificial neural network algorithm, and has been applied in many fields (Elahi et al. 2019). And some scholars have begun to use BP neural network to predict carbon emissions (Dong et al. 2018a; Hu et al. 2020; Li and Gao 2018).

**Genetic algorithm**

Genetic algorithm (GA) was first proposed by John Holland in the USA in the 1970s. The algorithm was designed and proposed according to the biological evolution law in nature. It is a computational model of biological evolution process simulating the natural selection and genetic mechanism of Darwinian evolution. Its essence is an efficient, parallel, and global search method, which can automatically acquire and accumulate the knowledge about the search space during the

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| Indicator | Coefficient | K    | F test | R²  |
|-----------|-------------|------|--------|-----|
| lnPP₁     | 0.059       | 0.27 | 0.000  |     |
| lnPP₂     | 0.106       | 0.000|        |     |
| lnPP₃     | – 0.15      | 0.984|        |     |
| lnPA₁     | 0.104       |      |        |     |
| lnPA₂     | 0.175       |      |        |     |
| lnPA₃     | 0.099       |      |        |     |
| lnPT₁     | 0.101       |      |        |     |
| lnPT₂     | – 0.167     |      |        |     |
```
search process and control the search process adaptively to get the optimal solution (Shen et al. 2011).

**GA-BP neural network**

GA can optimize the initial weights and thresholds of BP neural network, thus enhancing the robustness of BP neural network. It is found that the BP neural network model improved by GA is better than the traditional BP model in terms of performance and accuracy (Wu et al. 2014). Therefore, GA-BP model is selected to predict carbon emissions in this paper.

**Test of model performance and error**

After the setting of system parameters in the neural network is completed, the GA-BP model is programmed and debugged on MATLAB software. System parameters and programming logic structure are optimized according to the training results to ensure that the model can reflect the actual situation of carbon emissions in Xinjiang.

The performance test results of GA-BP model are shown in Fig. 3 and 4:

![Fig. 3 Performance comparison of BP-GA method in Xinjiang carbon emission prediction](image)

![Fig. 4 Performance analysis of the BP-GA method in the training, testing, and validation phases](image)
Fig. 2 and 3 show that the GA-BP model has good performance and is suitable for prediction. Meanwhile, the mean square error of the model is 0.2374, which is small, so the GA-BP prediction results fully meet the accuracy requirements.

**Scenario assumptions** In this paper, scenario analysis is adopted to design the development scenario of carbon emission in Xinjiang. Before the analysis of carbon emission scenario, the development scenario of influencing factors should be set, including 8 influencing factors of carbon emission as the indicators of scenario setting. Carbon emission scenarios are set according to the possible development trend of indicators. One is the middle scenario (middle scenario), which combines the official policies of the Chinese government and the analysis results of domestic and foreign experts as scenario parameters. One is the low-carbon scenario, which considers the impact or inhibition of other factors or events on the change of relevant indicators. The final category is the high-carbon scenario, where indicators change more than expected. Through the three scenarios design of each influencing factor, the combination of various influencing factors is formed.

**Scenario setting**

(1) Aging

According to the seventh national Census in 2020, 13.5% of the population in China is over 65 years old, indicating a deeper aging of the population. However, Xinjiang’s population aged over 65 is far lower than the national level at 7.76%, which is only higher than Tibet among 31 provinces in China. The aging trend in Xinjiang has slowed down. This is related to the family planning policy of national minorities in Xinjiang is more relaxed than Han nationality. The family planning policy of national minorities, on the basis of Han nationality, can have one more child, which has effectively curtailed the deepening of aging. By 2030, the proportion of Xinjiang’s population over 65 years old was about 9.8% and will reach 16.7% by 2050 (Chen et al. 2020). The setting of change rate of aging development scenario in Xinjiang is shown in Table 4.

(2) Urbanization

By the end of 2020, Xinjiang’s urbanization level was 52.4%. It ranked 26th among 31 provinces (excluding Hong Kong, Macao and Taiwan), lower than the national average of 60.6%. According to the 2020 report on the work of the Government of Xinjiang during the two sessions, by 2025, more than 60% of Xinjiang’s permanent residents will be urbanized (www.xinjiang.gov.cn). According to the Urban System Planning of Xinjiang (2012-2030), the urban population of Xinjiang will reach 66–68% of the total population by 2030. In this paper, 67% is taken (xjdr.xinjiang.gov.cn). On account of the plan, 75% of Xinjiang will be urbanized by 2050. The setting of the change rate of urbanization rate development scenario in Xinjiang is shown in Table 5.

(3) Household size

The change of family size is special, and there are special rules of change. By looking at the pattern of change in developed countries, there is a minimum of average family size. The average household size in the USA is 2.5 (Jiang and O'Neill 2007). Combined with the change law in developed countries (Bongaarts 2001) and the forecast results of domestic scholars (Jiao et al. 2019; Li et al. 2017), by 2030, the average family size of Xinjiang residents will be between 2.4 and 2.6, and then, it will be stable. This paper sets the middle value as 2.6 in 2030 and 2.4 in 2050. The setting of the change rate of household size development scenario in Xinjiang is shown in Table 6.

(4) Per capita GDP

By the end of 2020, Xinjiang’s per capita GDP had reached 53,371 Yuan, equivalent to 7738 US dollars. Due to the impact of the epidemic, Xinjiang’s per capita GDP has decreased compared to 2019. With the transformation of the traditional economic growth model, China’s economic growth rate began to fall from 2012, saying goodbye to the past high annual growth

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**Table 4** Scenario setting of aging development in Xinjiang

| Scenario            | 2020–2030 | 2031–2050 |
|---------------------|-----------|-----------|
| Low-carbon scenario | 2.26%     | 2.55%     |
| Middle scenario     | 2.36%     | 2.65%     |
| High-carbon scenario| 2.46%     | 2.75%     |

**Table 5** Urbanization development scenario in Xinjiang

| Scenario              | 2020–2025 | 2026–2030 | 2031–2050 |
|-----------------------|-----------|-----------|-----------|
| Low-carbon scenario   | 2.55%     | 2.03%     | 0.37%     |
| Middle scenario       | 2.75%     | 2.23%     | 0.57%     |
| High-carbon scenario  | 2.95%     | 2.43%     | 0.77%     |

**Table 6** Development scenario of household size in Xinjiang

| Scenario       | 2020–2030 | 2031–2050 |
|----------------|-----------|-----------|
| Low-carbon scenario | – 1.81%  | – 0.61%  |
| Middle scenario     | – 1.51%  | – 0.40%  |
| High-carbon scenario | – 1.23%  | – 0.20%  |
rate of about 10%. In recent years, China’s economy still maintains a medium-high growth rate of 6–8%. Among the major economies in the world, China is the only one with positive growth amid the global impact of COVID-19. According to the goal of realizing socialist modernization by 2035, China’s per capita GDP is expected to double that of 2020. This requires that per capita GDP growth in 2020–2035 should not be lower than 5%. The World Bank and the Development Research Centre of the State Council believe China will maintain an average annual GDP growth rate of 5.9% between 2021 and 2025 and 5% between 2026 and 2030 (He 2014). China has emerged from the COVID-19 pandemic earlier than most, and the INF forecasts that China’s growth rate will exceed 8% in 2021. As a province with relatively poor economic development in China, Xinjiang has a large number of people just lifted out of poverty and has a good growth potential. In the future, the per capita GDP growth of Xinjiang will be higher than the national average level. The development scenario change rate of Xinjiang’s per capita GDP is set as shown in Table 7.

(5) Number of vehicles

Motor, especially household cars, the direction of emission reduction is mainly to the transition to new energy vehicles. New energy vehicles have a significant carbon emission reduction effect than traditional cars (Chen 2019; Pan et al. 2020). Xinjiang’s current vehicle fleet is almost entirely fuel-powered. The number of new energy vehicles accounted for less than 0.3% (Li 2019). There are several difficulties in the transformation from traditional vehicles to new energy vehicles in Xinjiang. Firstly, the construction of public charging facilities in Xinjiang is very slow. After years of development, relevant facilities are still not complete; secondly, Xinjiang is large and sparsely populated, and many deserts, gobi, mountainous, long journey, and complex road conditions, the current new energy vehicles cannot fully meet the above driving needs. Thirdly, Xinjiang residents have a preference for cross-country vehicle or SUVs. In combination with the above situation, the scenario setting of the change rate of automobile quantity in Xinjiang is shown in Table 8.

(6) Per capita consumption of mutton

In Xinjiang, people’s demand for mutton, there is such a process of change. In the first stage, when the economy is underdeveloped and personal income is not high, the consumption of all kinds of meat is low. In the second stage, with the growth of economy and income, the consumption of lamb began to increase, while the demand for beef remained low due to the higher-price. Xinjiang is located in arid areas and far from the sea, so the consumption of aquatic products is very low. In the third stage, when economic development reached a certain level and residents could meet their own needs for mutton, the diet structure began to change. Due to the upper limit of the human body’s demand for protein, Xinjiang residents will start to consume more beef, and with the development of logistics and storage, seafood has also begun to be accepted on a large scale. At this point, per capita consumption of mutton will stop growing or even start to decline. There is a global push to reduce meat consumption and switch to plant-based protein to reduce the impact on the environment. However, due to natural conditions and food traditions, it is difficult to popularize this idea or movement in Xinjiang (Yin et al. 2020). At present, Xinjiang’s meat consumption is in the third stage, and the growth rate of per capita mutton consumption in the past 10 years is very low, only 0.8%. Xinjiang’s per capita mutton consumption is expected to peak by 2025 and begin to decline. The scenario setting of per capita mutton consumption in Xinjiang is shown in Table 9.

(7) Education level

Data from the sixth National census in 2010 showed that 2.315% of Xinjiang’s population had a college education. By the time of the seventh national census in 2020, it had increased to 16.536%. The average annual growth rate is 21.73%. At present, the proportion of

| Table 7 | Development scenario of Xinjiang’s per capita GDP |
|---------|-----------------------------------------------|
|         | 2020–2025 | 2025–2035 | 2036–2050 |
| Low-carbon scenario | 5.7% | 5.1% | 3.9% |
| Middle scenario | 5.9% | 5.3% | 4.0% |
| High-carbon scenario | 5.1% | 5.5% | 4.1% |

| Table 8 | Development scenario of number of vehicles in Xinjiang |
|---------|--------------------------------------------------------|
|         | 2020–2030 | 2031–2050 |
| Low-carbon scenario | 3.07% | 1.0% |
| Middle scenario | 3.77% | 1.5% |
| High-carbon scenario | 4.44% | 2.0% |

| Table 9 | Development scenario of per capita mutton consumption in Xinjiang |
|---------|---------------------------------------------------------------|
|         | 2020–2025 | 2026–2035 | 2036–2050 |
| Low-carbon scenario | 0.75% | – 1.3% | 0% |
| Middle scenario | 0.8% | – 1.1% | 0% |
| High-carbon scenario | 0.85% | – 0.9% | 0% |
China’s population with higher education is still much lower than that of developed countries. Chen et al. (2020) predicted that by 2035, the proportion of Xinjiang’s population with college education would be 23.64%, and by 2050, it would be 35.22%. The forecast is conservative. By 2035 and 2050, a lot of people will die in the 50s, 60s, and 70s, most of them with only a primary school or junior high school education. The scenario setting of education level in Xinjiang is shown in Table 10.

### Table 10 Development scenario of Education level in Xinjiang

| Scenario                  | 2020–2035 | 2036–2050 |
|---------------------------|-----------|-----------|
| Low-carbon scenario       | 2.41%     | 1.39%     |
| Middle scenario           | 3.73%     | 2.29%     |
| High-carbon scenario      | 4.85%     | 3.09%     |

Before 2003, coal accounted for more than 90% of Xinjiang’s direct energy consumption. By 2017, the share of coal in urban direct energy consumption had dropped to 18%, owing to a project launched in 2012 to switch from coal to natural gas. However, coal still accounts for 88% of rural household direct energy consumption (Chai et al. 2021). Therefore, the future energy transformation of the residential sector is mainly concentrated in rural areas. In the future, the main measures for rural carbon reduction are to replace coal with natural gas, coal with electricity, and increase the proportion of biomass and photovoltaic energy. But the costs of carbon reduction cannot be ignored. Although coal to natural gas can significantly reduce carbon emissions, the cost of the rise cannot be ignored. Natural gas normally increases rural household fuel spending by an average of 65–80%, which can worsen the financial situation of poor households (Li et al. 2021). The cost of reforming rural Xinjiang from coal to gas has been greater than in other northern regions. Because Xinjiang area is large, rural distribution is scattered, especially southern Xinjiang area. Therefore, for rural Xinjiang, the most realistic approach is to use photovoltaic energy. The scenario setting of household direct energy consumption structure is shown in Table 11.

### Table 11 Development scenario of Household direct consumption of energy structure

| Scenario                  | 2020–2030 | 2031–2050 |
|---------------------------|-----------|-----------|
| Low-carbon scenario       | – 1.427%  | – 10.76%  |
| Middle scenario           | – 0.924%  | – 7.07%   |
| High-carbon scenario      | – 0.449%  | – 3.35%   |

2020–2050 are set as low (L), middle (M), and high (H). Then, three sub-scenarios are set in the broad category of scenarios, totaling nine development scenarios. The descriptions are as follows (Table 12).

### Prediction results

The parameters of nine scenarios are input into the GA-BP model to simulate the development trend of emissions, and the carbon emission data of different development scenarios in 2020–2050 are obtained. The carbon emission trends of nine different scenarios are depicted, as shown in Fig. 5.

Obviously, it can be seen from Fig. 4 that there are significant differences in peak carbon emissions under different scenarios, which are H2, H1, M3, M2, L3, M1, L2, and L1 in descending order. H3 will not peak until 2050. In general, peak carbon emissions are the result of a combination of inhibiting effects caused by negative factors and promoting effects caused by positive factors.

In the three cases of the middle scenario, the earliest peak time is 2032, and the latest peak time is 2037, both of which are later than the national requirement of reaching the peak in 2030. However, considering the actual situation in Xinjiang, it is acceptable for M1 and M2 to peak in 2032 and 2035, respectively. That is because some developed parts of China will peak around 2025 (Liu et al. 2020).

In the low-carbon scenario, L1, L2, and L3 peak in 2033, 2029, and 2030, respectively. L1 has the smallest peak although the peak time is the latest. The peak time difference of L2 and L3 is only 1 year, but the peak difference of L3 is extremely large, and the peak value of L3 is larger than that of M1, so L3 is relatively undesirable. L2 peaks early and takes a long time to decarbonize, giving it a time advantage to achieve carbon neutrality. The peak time of L3 is late, but the peak value of L3 is small, and the difficulty of carbon reduction is low.

In the high-carbon scenario, H3 cannot reach its peak, indicating that the negative factors mainly based on the energy structure of residents’ direct consumption cannot offset the growth of carbon emission caused by the change of population factor. H2 peaked in 2048, but it is not known whether it continued to decline after 2050. The peak time of H1 is 2038, and the carbon emission decreases slowly
after the peak, indicating that the positive factors causing the growth of carbon emission still have a strong promoting role.

From the perspective of population factors, the carbon peak time in Xinjiang is relatively late. It may be that the change of population factors leads to the lag of the change of carbon emissions. Based on the results of this paper, household size and the household direct consumption energy structure will be a reluctant way to curb carbon emissions. Only if these two changes substantially can the increase in carbon emissions be effectively suppressed. At present, the two indicators of aging and urbanization still play a promoting role, but the future trend of development and the response of carbon emissions to it still need to be further studied. Per capita GDP and the number of vehicles will always be strong promotors. Xinjiang is, after all, a less developed province, and it is almost a given that economic growth will lead to increased carbon emissions (Wang and Su 2020). Based on the current situation of Xinjiang, in fact, the vehicles in Xinjiang will not be completely replaced by new energy vehicles in the future. The remote distance between cities, a large number of mountains, deserts and gobi, lead to the current new energy vehicles will hardly be considered, unless the technological breakthrough is achieved, can guarantee ultra-long-distance driving and adapt to special terrain, and the price has advantages over traditional cars. The change of diet is the change of concept and economy. With the opening of concept, the progress of warehousing and logistics, and the increase of income, the diet will inevitably develop towards the direction of sustainability. Xinjiang’s education has been booming in recent years. The government has stepped up efforts to support higher education, and 12-year compulsory education has been realized in some parts of Xinjiang. There is a large overlap between the people with high education level and the middle class. Therefore, before the concepts of low-carbon life and green life are introduced to this group, carbon emissions will inevitably increase.

Compared with (Zuo et al. 2020) the result of this paper has a similar conclusion that Xinjiang cannot achieve carbon peak before 2030. Furthermore, this study and Teng et al. (2019) agree that cars and food are important drivers in the future. But, Fang et al. (2019) believed that Xinjiang could achieve carbon peak before 2030 under different scenarios, which may be caused by different research perspectives. However, we agree that the earliest peak scenario may not be the best choice, because the feasibility issue must be considered to take the appropriate path, rather than blindly choose the earliest peak path.

**Conclusion and policy recommendations**

**Conclusion**

Using the time series data of Xinjiang from 2000 to 2019, this paper studied the impact of population-related factors on carbon emissions in Xinjiang. The STIRPAT model is used to analyze the impact of various indicators on carbon emissions. It is concluded that the number of vehicles is the biggest positive factor affecting carbon emissions, and urbanization, per capita GDP, education level, and per capita mutton consumption play a large role in promoting carbon emissions. The effect of aging is less obvious. Household size and direct energy consumption structure of residents have a significant inhibitory effect on carbon emissions. Based on STIRPAT model, GA-BP neural network is introduced to predict carbon emission. The forecast results show that the time of carbon peak is later in the perspective of population related factors. If the peak is reached before 2030, the conditions of scenario assumptions are more demanding. In the low-carbon and middle scenarios, the peak time is distributed between 2029 and 2037, which is acceptable for Xinjiang, while in the high-carbon scenario, the peak time is very late, or even not before 2050.
Policy recommendations

Based on the research of this paper, from the perspective of policy, the government should formulate reasonable policies according to the changes of various population factors and different periods, respect the internal law of the impact of population factors on carbon emissions, and coordinate the relationship between good people and the environment. In the process of urbanization, it is very important to build low-carbon cities. The increase in the number of small households and the change in the structure of household direct consumption of energy can effectively reduce carbon emissions. With the development of economy and the improvement of education level, we should strengthen the publicity of low-carbon life, vigorously promote low-carbon products, and guide people with high education and middle and high income to implement low-carbon life, so as to achieve the emission reduction target. But as life expectancy increases, the impact of aging on carbon emissions should attract more attention. Above all, encourage the innovative development of green technologies and promote clean energy, such as solar energy, which has great potential, especially in the household sector. Vigorously develop new energy vehicles adapted to Xinjiang and gradually reduce dependence on fossil fuels. Nevertheless, this study is preliminary and exploratory in nature and can be used as a reference for government planning. This article also has the inadequacy. Limited by energy and data, there are other factors that were not analyzed, such as consumption patterns, the ratio of men to women, and housing size. All of these effects on Xinjiang’s carbon emissions are worth studying. In the future, we will continue to conduct in-depth research on carbon emissions in Xinjiang in order to cope with the pressure of carbon emission reduction.

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Author contribution

Zhibibula·Simayi: Funding acquisition. Chai Ziyuan: Methodology, Formal analysis, Software, Data curation, Writing—original draft, Visualization. Yan Yibo: Conceptualization, Project administration. Maliyamuguli·Abulimiti: Writing—review and editing. Yang Shengtian: Supervision. Wang Yuqing: Data

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Availability of data and materials

The datasets used and/or analyzed during the current study are available from the corresponding author on reasonable request. The data used in this study can be found in various statistical yearbooks of China.

Declarations

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Not applicable

Consent for publication

All the authors agreed to be published and open access

Competing interests

The authors declare no competing interests.
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