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An Analysis Based on SD Model for Energy-Related CO_2 Mitigation in the Chinese Household Sector

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Abstract: Reducing carbon dioxide (CO_2) emissions has become a global consensus in response to global warming and climate change, especially to China, the largest CO_2 emitter in the world. Most studies have focused on CO_2 emissions from the production sector, however, the household sector plays an important role in the total energy-related CO_2 emissions. This study formulates an integrated model based on logarithmic mean Divisia index methodology and a system dynamics model to dynamically simulate household energy consumption and CO_2 emissions under different conditions. Results show the following: (1) the integrated model performs well in calculating the contribution of influencing factors on household CO_2 emissions and analyzing the options for CO_2 emission mitigation; (2) the increase in income is the dominant driving force of household CO_2 emissions, and as a result of the improved standard of living in China a sustained increase in household CO_2 emissions can be expected; (3) with decreasing energy intensity, CO_2 emissions will decrease to 404.26 Mt-CO_2 in 2020, which is 9.84% lower than the emissions in 2014; (4) the reduction potential by developing non-fossil energy sources is limited, and raising the rate of urbanization cannot reduce the household CO_2 emission under the comprehensive influence of other factors.

Keywords: CO_2 emissions; household sector; system dynamics

1. Introduction

Carbon dioxide (CO_2), which is the prominent greenhouse gas that can result in global warming and climate change, has caused widespread concern in the international community [1]. Many scholars have conducted considerable research on CO_2, such as the measurement of regional CO_2 emission amounts and analyses of its evolution trends [2,3], relationships between population, economy and CO_2 emissions [4], the influencing factors of energy consumption and CO_2 emission [5–7], and policies to reduce CO_2 emissions [8,9].

China, the largest CO_2 emitter in the world, is facing intense pressures to cut its CO_2 emissions. During the Copenhagen Climate Change Conference in 2009, the Chinese government committed to reduce its CO_2 emissions per unit of the gross domestic product (GDP) in 2020 by 40% to 45% relative to 2005 levels. After the industry and transportation sectors, the household sector has the most significant influence on the total energy-related CO_2 emissions [10]. Reducing household CO_2 emissions has attracted increasing attention, and several studies have quantified household CO_2 emissions for various countries, such as Italy [11], USA [12], UK [13], Ireland [14] and China [15–17].

Regional CO_2 emissions are also a complex system problem that involves human activity, economic development, energy mix, policy orientation, and other factors [18]. Therefore, integrating the main influencing factors and analyzing the CO_2 emission behavior from the perspective of system dynamics are necessary.

The decomposition of CO_2 emission has been an actively researched topic. Logarithmic mean Divisia index (LMDI) is the most preferred and widely used methodology to quantify the impact of different factors on the change of energy consumption and CO_2 emissions owing to its solid theoretical foundation, adaptability, ease of use, interpretation of results, and other desirable properties in the context of decomposition analysis [19].

Researchers have applied LMDI methodology to decompose the effects of changes in CO_2 emissions from the global [20,21], national [22–25], and sectoral [26–28] perspectives, and divide the factors into energy mix, energy intensity, industrial structure, economic activity, and population scale. Wang et al. [22] analyzed the change of aggregated CO_2 emissions in China and revealed that fuel switching and energy penetration exhibited positive effects on the decrease of CO_2 emissions. Shahiduzzaman and Alam [23] decomposed the energy intensity of Australia and indicated that energy efficiency played a dominant role in reducing energy intensity and CO_2 emissions in that country. Zhou et al. [26] analyzed the relationship between industrial structural transformation and CO_2 emissions in China and found that promoting the upgrade and optimization of industrial structure through technical progress is an effective way to reduce a region's CO_2 emissions. Li et al. [27] explored the impact of factors on the CO_2 emissions from road freight transportation in China and found that economic growth is the most important factor in increasing CO_2 emissions. By contrast, they found that the ton kilometer per value added of industry and the market concentration level contribute significantly to the decrease of CO_2 emissions. Moutinho et al. [28] identified relevant factors on the changes of CO_2 emissions of European countries and found that CO_2 emissions are correlated with the energy consumption of the economy, which is determined by the change of population.

LMDI methodology offers reasonable driving forces of energy-related CO_2 emissions from the household sector. However, CO_2 emission is a complex issue that cannot be accurately analyzed by a single LMDI methodology [29]. Thus, a system dynamics (SD) model was added to solve complex and time-varying problems.

The SD model was initially created in 1956 by Forrester at the Massachusetts Institute of Technology as a methodology for modeling, simulating, and analyzing a complex system [30,31]. Its main goal is to understand how a given system evolves [32]. In particular, the SD model has a distinct advantage in analyzing, improving, and managing the system characterized by a long development cycle and complex feedback effects [33], which has been widely applied in studies on economy, society, ecology, and various complex systems [34–36].

Recently, an increasing number of publications have focused on the application of SD models to CO_2 emissions. Ansari and Seifi [37] developed an SD model to analyze energy consumption and CO_2 emission in the Iranian cement industry. Saysel and Hekimoğlu [38] proposed an SD model to explore the options for CO_2 mitigation in the Turkish electric power industry. Li et al. [39] established an SD model to find the improvement of CO_2 emission reduction policies in a traditional industrial region.

Therefore, an integrated model based on LMDI methodology and SD model is built in this study. The purpose of this work is to: (1) investigate the driving forces of energy-related CO_2 emissions in the household sector and (2) analyze the options for household CO_2 emission mitigation in China to help the government formulate future CO_2 emission reduction policies.

The rest of this paper is organized as follows: Section 2 introduces the research methodology. Section 3 presents the date used. Section 4 discusses the main results of this study. Section 5 concludes the study and proposes policy recommendations to mitigate household CO_2 emissions in China.

2. Methodology

In order to reveal the dynamical mechanism of household CO_2 emissions, an integrated model named LMDI-SD model (Figure 1) is built in this study.

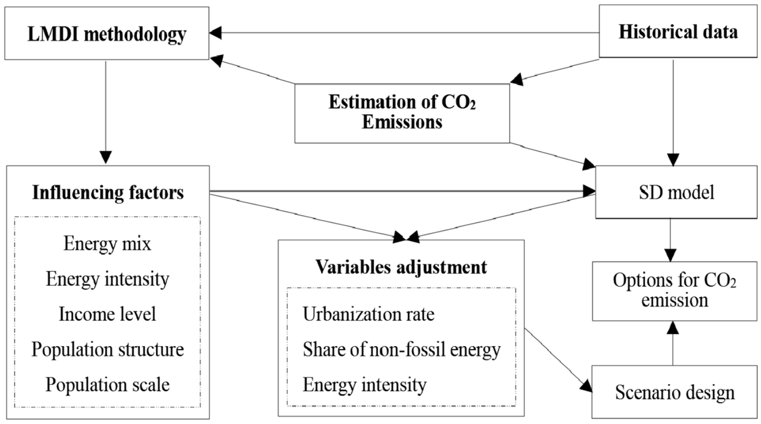

Figure 1. Model structure overview.

The construction thinking and operating sequence of LMDI-SD model are as follows:

(1) Step 1: Estimation of CO_2 Emissions

The methodology described in the 2006 Intergovernmental Panel on Climate Change Guidelines for National Greenhouse Gas Inventories [40] indicates that energy-related CO_2 emissions in a given year may be estimated as follows:

$$C_{tot} = \sum_{ij} C_{ij} = \sum_{ij} E_{ij} \times F_i \times K \quad (1)$$

where C_{tot} represents the total amount of household CO_2 emissions, subscripts i represents the energy type, such as coal, petroleum and natural gas, subscripts j represents urban and rural household, C_{ij} represents the amount of CO_2 emissions based on energy type i by household sector j, E_{ij} is the energy consumption based on energy type i by household sector j, and F_i is the coefficient of CO_2 emissions of the ith energy type. The coefficient of CO_2 emissions (F_i) is given by the Energy Research Institute of the National Development and Reform Commission. Here, the coefficient of coal, petroleum, and natural gas are 0.7476, 0.5825, and 0.4435 $t \cdot tce^{-1}$, respectively. K is the molecular weight ratio of CO_2 to carbon (44/12).

(2) Step 2: Decomposition of CO_2 Emissions

By investigating the influencing factors of energy-related CO_2 emission in household sectors by LMDI methodology proposed by Ang [41], we may preliminarily propose CO_2 emission reduction policies. The energy-related CO_2 emissions establish the following decomposition model:

$$C_{tot} = \sum_{ij} \frac{C_{ij}}{E_{ij}} \times \frac{E_{ij}}{E_j} \times \frac{E_j}{I_j} \times \frac{I_j}{P_j} \times \frac{P_j}{P} \times P = \sum_{ij} CF \times E_{str} \times E_{\text{int}} \times I_{lev} \times P_{str} \times P \quad (2)$$

where C_{tot} represents the total amount of household CO_2 emissions, subscripts i represents the energy type, such as coal, petroleum, natural gas and non-fossil energy, subscripts j represents urban and rural household, C_{ij} represents the amount of CO_2 emissions based on energy type i by household sector j, E_{ij} represents the amount of energy consumption based on energy type i by household sector j, E_j represents the total energy consumption of the jth household sector, I_j represents the total disposable income of the jth household sector, P_j represents the population of the jth household sector, and P

represents the total population. $CF = C_{ij}/E_{ij}$ represents the CO_2 emission factor for energy type i by household sector j, $E_{str} = E_{ij}/E_j$ represents the proportion of the total energy consumption by household sector j accounted for by the consumption of energy type i, $E_{int} = E_j/P_j$ represents the energy intensity of household sector j, $I_{lev} = I_j/P_j$ represents the per capita disposable income of household sector j, and $P_{str} = P_j/P$ represents the proportion of the total population accounted for by the population of household sector j.

The changes in energy-related CO_2 emissions from years $t-1$ to t can be calculated using the following equation:

$$\Delta C_{tot} = C^t - C^{t-1} = \Delta C_{CF} + \Delta C_{E_{str}} + \Delta C_{E_{\text{int}}} + \Delta C_{I_{lev}} + \Delta C_{P_{str}} + \Delta C_P \tag{3}$$

where subscripts t and $t-1$ denote the values for years t and $t-1$ respectively; ΔC_{tot} denotes the changes in household CO_2 emissions from years $t-1$ to t; C^t and C^{t-1} denote the total CO_2 emissions in years t and $t-1$ respectively; and ΔC_{CF}, ΔC_{Estr}, ΔC_{Eint}, ΔC_{Ilev}, ΔC_{Pstr}, and ΔC_P refer to the contribution of CO_2 emission factors, energy mix, energy intensity, income level, population structure, and population scale, respectively.

The CO_2 emission factors for different energy types in this study are constant. Therefore, the contribution of CO_2 emission factors (ΔC_{CF}) on the decomposition is always zero. These factors have changed over time because of the changes in fuel quality, but these changes are extremely minimal, such that they are negligible in the analysis of macro changes in CO_2 emissions [42]. Thus, Equation (3) can be rewritten as follows:

$$\Delta C_{tot} = \Delta C_{E_{str}} + \Delta C_{E_{\text{int}}} + \Delta C_{I_{lev}} + \Delta C_{P_{str}} + \Delta C_P \tag{4}$$

When additive decomposition is applied, the CO_2 factors for the consumption of energy type i by household sector j can be decomposed as follows:

$$\Delta C_{E_{str}} = \sum_{\text{ij}} L\left(C_{ij}^t, C_{ij}^{t-1}\right) \ln\left(\frac{E_{str}^t}{E_{str}^{t-1}}\right), \tag{5}$$

$$\Delta C_{E_{\text{int}}} = \sum_{ij} L\left(C_{ij}^t, C_{ij}^{t-1}\right) \ln\left(\frac{E_{\text{int}}^t}{E_{\text{int}}^{t-1}}\right), \tag{6}$$

$$\Delta C_{I_{lev}} = \sum_{ij} L\left(C_{ij}^t, C_{ij}^{t-1}\right) \ln\left(\frac{I_{lev}^t}{I_{lev}^{t-1}}\right), \tag{7}$$

$$\Delta C_{P_{str}} = \sum_{ij} L\left(C_{ij}^t, C_{ij}^{t-1}\right) \ln\left(\frac{P_{str}^t}{P_{str}^{t-1}}\right), \tag{8}$$

$$\Delta C_P = \sum_{ij} L\left(C_{ij}^t, C_{ij}^{t-1}\right) \ln\left(\frac{P^t}{P^{t-1}}\right), \tag{9}$$

where function $L(x, y)$ is the logarithmic average of the two positive numbers x and y, which are defined as:

$$L(\mathrm{x}, y) = \begin{cases} (x-y)/(\ln x - \ln y), & x \neq y \\ x, & x = y \\ 0, & x = y = 0 \end{cases} \tag{10}$$

In order to calculate the contribution of each effect on total amount of CO_2 emissions, we form:

$$\left(\frac{\Delta C_{E_{str}}}{\Delta C} + \frac{\Delta C_{E_{\text{int}}}}{\Delta C} + \frac{\Delta C_{I_{lev}}}{\Delta C} + \frac{\Delta C_{P_{str}}}{\Delta C} + \frac{\Delta C_P}{\Delta C}\right) \times 100\% = 100\% \tag{11}$$

(3) Step 3: Developing the SD model

We building the SD model of household CO_2 emission with the software Vensim PLE (Ventana Systems, Inc., Harvard, MA, USA) according to the main influencing factors of CO_2 emissions. Then we simulate the scenarios by implementing different CO_2 reduction policies, obtaining the options for household CO_2 emission mitigation.

3. Data Description

Considering the availability of data, this study classifies all fossil energy into three types—coal, petroleum, and natural gas—which constitute 93.35% of the total primary energy consumption in China according to the BP Statistical Review of World Energy [43]. Moreover, thermal power and heat are secondary energy sources that have been calculated based on the type of fuel consumed to generate electricity and heat. Thus, the present study considers only hydropower, wind power, solar power, and nuclear power and defines them as non-fossil energy to avoid tautologically calculating the consumption of coal, petroleum, and natural gas in the electricity generation process [10]. The data on energy consumption used in this study mainly come from the China Energy Statistical Yearbooks 2001–2015 [44–58], while the CO_2 emission factors of each energy type are given by the Energy Research Institute of the National Development and Reform Commission of China. The data on population and income come from the China Statistical Yearbooks 2001–2015 [59–73]. Calorific value, population, disposable income, energy consumption, and CO_2 emission data are calculated in billion person, yuan at constant prices in 2005, million tons of coal equivalent (Mtce), and million tons (Mt-CO_2), respectively.

4. Results and Discussion

4.1. Estimation of Household CO_2 Emissions

The resultant household CO_2 emissions in China over the period 2000–2014 based on Equation (1) are presented in Figure 2. The aggregate CO_2 emissions increased from 225.84 Mt-CO_2 in 2000 to 448.36 Mt-CO_2 in 2014 as a result of an annual growth rate of 5.02%. The CO_2 emissions based on coal increased from 172.45 Mt-CO_2 in 2000 to 198.23 Mt-CO_2 in 2014, which indicated a relatively stable amount. However, the CO_2 emissions based on petroleum and natural gas rapidly increased. The result shows that by 2014 the CO_2 emissions based on petroleum and natural gas increased 3.83 and 10.36 times (relative to 2000) respectively owing to the proportion of energy consumption, which accounted respectively for the petroleum and natural gas increase of 1.59 and 4.3 times in 2000.

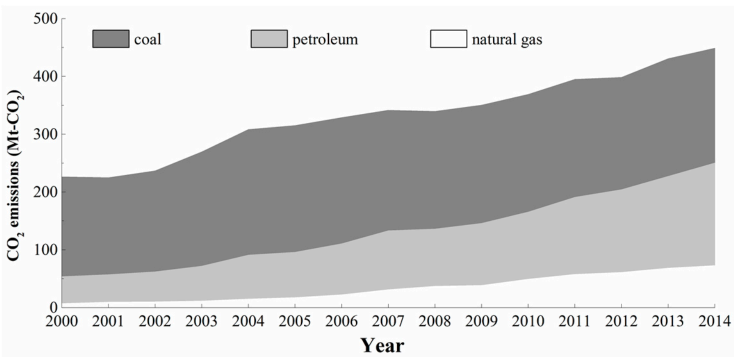

Figure 2. Household CO_2 emissions of different energy types in China (2000–2014).

Figure 3 illustrates that the CO_2 emissions from urban and rural households continuously increased from 112.96 Mt-CO_2 and 112.89 Mt-CO_2 in 2000 to 233.5 Mt-CO_2 and 214.85 Mt-CO_2 in 2014, respectively. The contribution of the total CO_2 emissions from urban and rural households are similar to each other, even though the total disposable income of urban households is 3.5 times more than that of rural households. This indicates that the energy intensity of urban households remains lower than that of rural households, and the reduction of the CO_2 emissions of rural households is relatively weak.

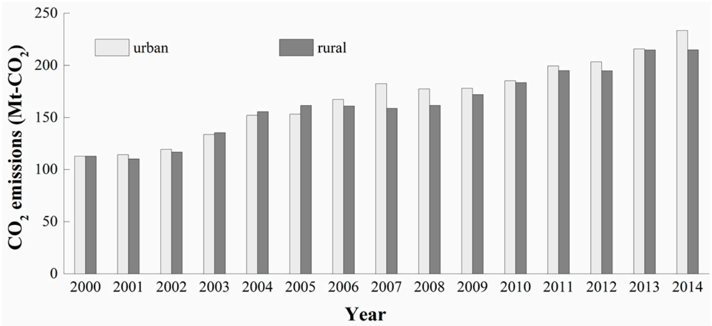

Figure 3. CO_2 emissions of different household sectors in China (2000–2014).

4.2. Decomposition Analysis

The influencing factors of household CO_2 emissions in China can be decomposed using Equation (3). The results, presented in Table 1, reveal that income level and population scale are the main drivers of CO_2 emissions, energy intensity and energy mix are the inhibitory factors that decreased CO_2 emissions, whereas population structure is a stimulatory factor at the beginning and then an inhibitory factor.

Table 1. Complete decomposition of changes in the household CO_2 emissions of China. (Mt-CO_2).

Period	ΔC_{Estr}	ΔC_{Eint}	ΔC_{Ilev}	ΔC_{Pstr}	ΔC_P
2000–2001	−333.43	−1224.98	1093.421	188.16	156.51
2001–2002	−73.84	−807.82	1730.825	172.10	148.64
2002–2003	34.35	1652.145	1285.22	156.15	151.61
2003–2004	−364.00	2693.77	1234.703	122.90	168.97
2004–2005	−372.69	−1288.33	2091.431	104.84	183.26
2005–2006	−365.16	−719.75	2160.56	108.87	169.64
2006–2007	−770.94	−804.088	2548.018	148.00	172.78
2007–2008	−789.09	−1817.37	2109.393	96.84	172.74
2008–2009	−403.36	−1590.27	2862.664	72.99	167.65
2009–2010	−664.04	327.6879	1988.50	31.42	172.01
2010–2011	−162.68	−105.153	2667.76	−4.51	182.64
2011–2012	−1085.80	−2630.17	3918.236	−22.84	196.23
2012–2013	−410.99	453.2044	3033.81	−49.41	203.76
2013–2014	−572.69	−1651.13	3837.076	−57.83	228.58

4.2.1. Impact Analysis of Energy Mix

Figure 4 reveals that the accumulated changes in household CO_2 emissions from the energy mix effect decreased to nearly 63.34 Mt-CO_2 from 2000 to 2014, accounting for 32.15% of the total changes in CO_2 emissions in absolute value. As shown in Figure 4, coal is no longer the major energy type for household CO_2 emissions in China. The proportion of total energy consumption accounted for by coal continuously decreased from 68.37% in 2000 to 32.65% in 2014. By contrast, between 2000 and 2014 that accounted for by petroleum increased from 23.61% to 37.57%, natural gas increased from 4.67% to 20.11%, and non-fossil energy source increased from 3.35% to 9.67%. Therefore, reducing fossil energy consumption and enhancing the applications of non-fossil energy sources are significant ways to mitigate CO_2 emissions. Acceleration of hydroelectric and nuclear power development is mentioned in the "13th Five-year Plan of Electicity Developmen" (from 2016 to 2020). The installed capacity of nuclear power will reach 58 GW by 2020, which increased 2.86 times (relative to 2014).

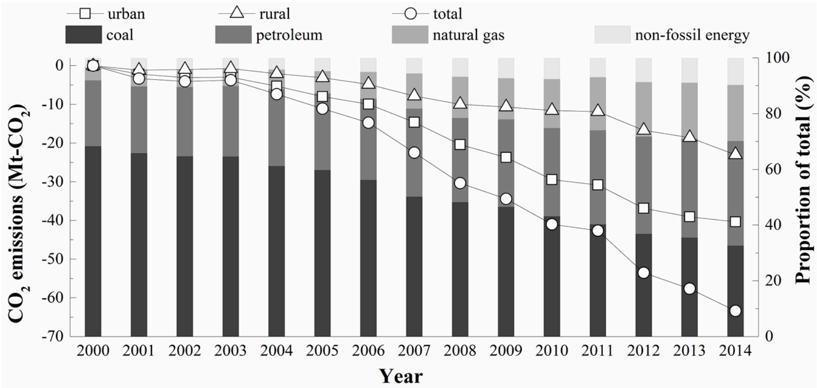

Figure 4. Accumulated changes in energy mix effect on household CO_2 emissions and energy mix in China (2000–2014).

In addition, the energy mix effect on CO_2 emissions from urban and rural decreased to 40.34 Mt-CO_2 and 23 Mt-CO_2, respectively. This indicates that the energy mix of urban households was more rational than that of rural households, which means that the reduction of CO_2 emissions in the former is more efficient than that in the latter.

4.2.2. Impact Analysis of Energy Intensity

The accumulated changes in household CO_2 emissions from the energy intensity effect from 2000 to 2014 decreased by 75.12 Mt-CO_2, which accounted for 38.13% of the total changes in CO_2 emissions in absolute value (Figure 5). The energy intensity of urban households decreased from 0.14 tce/10^4 yuan in 2000 to 0.08 tce/10^4 yuan in 2014, whereas the energy intensity of rural households increased from 0.2 tce/10^4 yuan in 2000 to 0.23 tce/10^4 yuan in 2014. Accordingly, the energy intensity effect on CO_2 emissions from urban households decreased by 82.31 Mt-CO_2, and that from rural households increased by 7.19 Mt-CO_2. A probable cause is that the series of energy-saving policies, which resulted in a decrease in the total amount of energy consumption, was more smoothly implemented in urban areas than in rural areas. Therefore, if other factors remain unchanged, then a decline in energy intensity reduces CO_2 emissions, and vice versa. In the future, using energy-efficient appliances and new energy vehicles is an efficient approach to reduce CO_2 emissions.

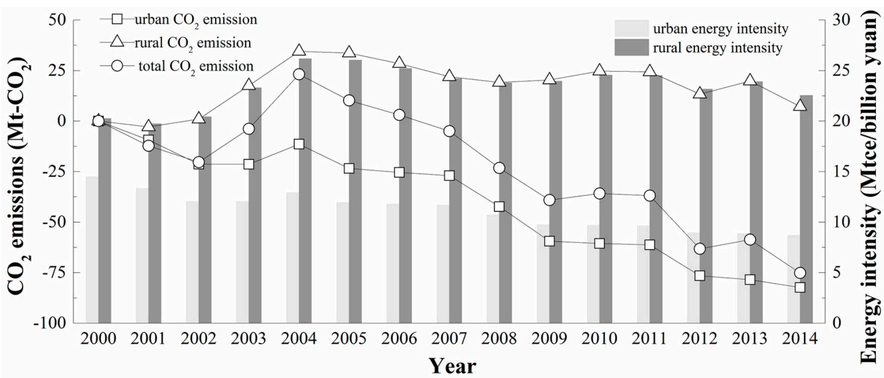

Figure 5. Accumulated changes in energy intensity effect on household CO_2 emissions and energy intensity in China (2000–2014).

4.2.3. Impact Analysis of Income Level

Figure 6 shows that the income level effect on household CO_2 emissions is positive and has the largest contribution to CO_2 emissions during the whole study period. The accumulated changes in CO_2

emissions from the income level effect between 2000 and 2014 increased by 325.62 Mt-CO_2, accounting for 165.27% of the total changes in CO_2 emissions in absolute value. The per capita disposable income of urban and rural households increased by 2.67 and 2.55 times, respectively, from 2000 to 2014. The rapid growth in the demand for home appliances and private car ownership increased the household energy consumption and CO_2 emissions to some extent as the income level and standards of living rose. In addition, although the total disposable income of urban households is 3.5 times more than that of rural households in 2014, the income level effect on CO_2 emissions from urban and rural households are similar to each other. This indicates that the energy intensity of urban households remains lower than that of rural households. The government should pay more attention to reducing the energy intensity and CO_2 emissions in rural households.

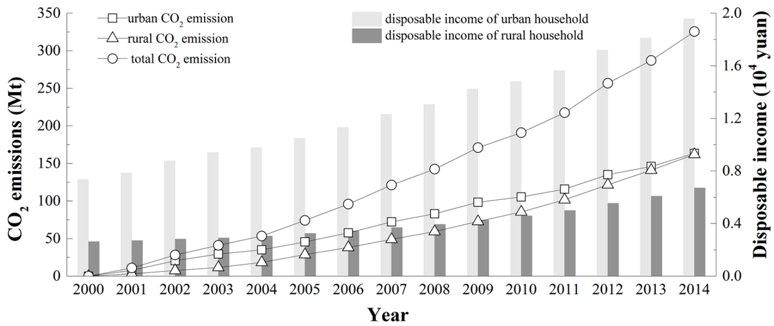

Figure 6. Accumulated changes in income level effect on household CO_2 emissions and income level in China (2000–2014).

4.2.4. Impact Analysis of Population Structure

The accumulated changes in household CO_2 emissions from the population structure effect increased by 10.68 Mt-CO_2 over the whole study period, accounting for 5.42% of the total changes in household CO_2 emissions in absolute value (Figure 7). The population structure effect on CO_2 emission from urban households increased by 67.16 Mt-CO_2, while that from rural households decreased by 56.48 Mt-CO_2 owing to the improvement of urbanization level. The urbanization rate of China gradually increased from 36.22% in 2000 to 54.77% in 2014, and the contribution of population structure effect to changes in household CO_2 emissions increased at the beginning and then began decreasing when China's urban population surpassed the rural population in 2011. Thus, the population structure effect plays an increasingly important role in inhibiting CO_2 emissions. If other factors remain unchanged, then an increase in urbanization rate reduces CO_2 emissions, and vice versa.

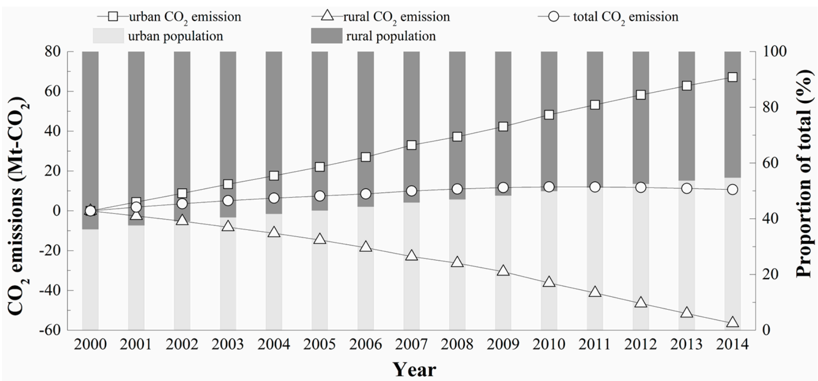

Figure 7. Accumulated changes in population structure effect on household CO_2 emissions and population structure in China (2000–2014).

4.2.5. Impact Analysis of Population Scale

Figure 8 reveals that the accumulated changes in CO_2 emissions from the population scale effect increased by 24.75 Mt-CO_2 from 2000 to 2014, contributing 12.56% to the total changes in CO_2 emissions in absolute value. The population of China increased from 12.67 billion persons in 2000 to 13.68 billion persons in 2014, which follows the average annual growth rates of 5.46‰ and is related to the family planning policy. This finding indicates that the expanding population scale of China increases household CO_2 emissions but is minimized by the income level effect. Given that the two-child policy has implemented by the Chinese government, the fertility rate in China is expected to increase and the population expansion effect on increasing CO_2 emissions will gradually be enhanced.

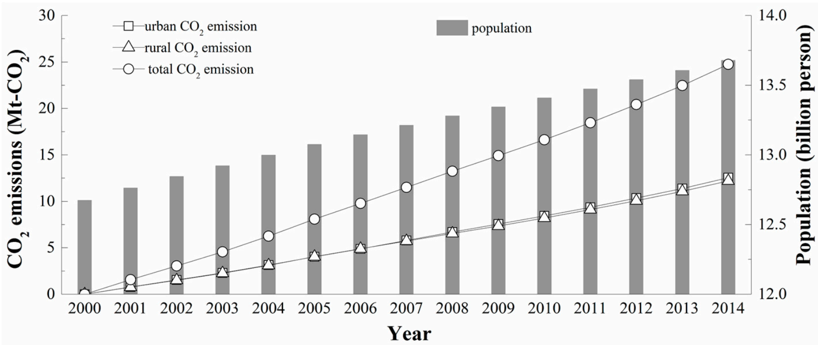

Figure 8. Accumulated changes in population scale effect on household CO_2 emissions and population in China (2000–2014).

4.3. Modeling Process

4.3.1. Establishment of the SD Model and Dynamic Simulation

LMDI methodology offers reasonable driving forces of energy-related CO_2 emissions from household sectors. The population and disposable income growth make the total energy consumption increase, and then causes the increase of fossil energy consumption and amount of CO_2 emissions. The decline in energy intensity would decrease the total energy consumption, and then reduce fossil energy consumption and amount of CO_2 emissions. Additionally, the strengthening of non-fossil energy sources implies a decrease of fossil energy consumption and CO_2 emission amount.

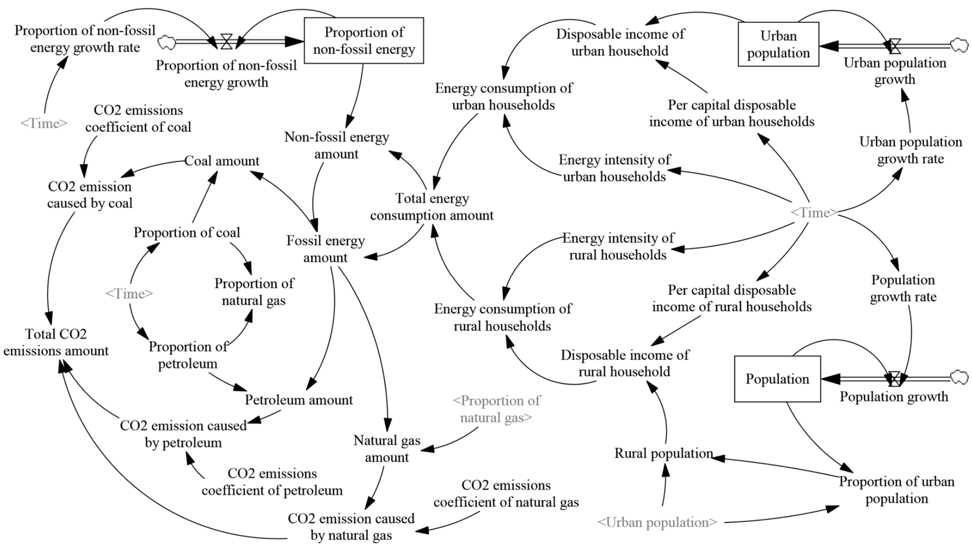

Figure 9. Stock-flow diagram for the SD model of household CO_2 emissions in China.

Considering the development characteristics of household sectors in China, the stock-flow diagram for the SD model of household CO_2 emissions is built by Vensim PLE software, which is composed of three level variables, three rate variables, and 31 auxiliary variables (Figure 9). The time step is one year. The simulation period extends from 2000 to 2020, although 2000 to 2014 is used to fix the parameters of the model and 2015 to 2020 corresponds to the forecast period of the model.

The variable types are listed in Table 2. The simultaneous differential equations in the stock-flow diagram are defined based on the actual data for household CO_2 emissions from 2000 to 2014 in China.

Table 2. Mathematical notations and nomenclatures.

Variable Type	Notation	Nomenclature	Unit
Level	P	Population	billion person
	UP	Urban population	billion person
	PRE	Proportion of non-fossil energy	%
Rate	PGR	Population growth rate	‰
	UPGR	Urban population growth rate	%
	PREGR	Proportion of non-fossil energy growth rate	%
Auxiliary	PG	Population growth	billion person
	UPG	Urban population growth	billion person
	RP	Rural population	billion person
	PUP	Proportion of urban population	%
	PCDIUH	Per capital disposable income of urban households	yuan/person
	PCDIRH	Per capital disposable income of rural households	yuan/person
	DIUH	Disposable income of urban households	billion yuan
	DIRH	Disposable income of rural households	billion yuan
	EIUH	Energy intensity of urban households	Mtce/billion yuan
	RIRH	Energy intensity of rural households	Mtce/billion yuan
	ECUH	Energy consumption of urban households	Mtce
	ECRH	Energy consumption of rural households	Mtce
	TECA	Total energy consumption amount	Mtce
	FEA	Fossil energy amount	Mtce
	REA	Non-fossil energy amount	Mtce
	PREG	Proportion of non-fossil energy growth	%
	CA	Coal amount	Mtce
	PC	Proportion of coal	%
	PA	Petroleum amount	Mtce
	PP	Proportion of petroleum	%
	NGA	Natural gas amount	Mtce
	PNG	Proportion of natural gas	%
	CECC	CO_2 emissions coefficient of coal	$t \cdot tce^{-1}$
	CECBC	CO_2 emission caused by coal	Mt-CO_2
	CECP	CO_2 emissions coefficient of petroleum	$t \cdot tce^{-1}$
	CECBP	CO_2 emission caused by petroleum	Mt-CO_2
	CECNG	CO_2 emissions coefficient of natural gas	$t \cdot tce^{-1}$
	CECBNG	CO_2 emission caused by natural gas	Mt-CO_2
	TCEA	Total CO_2 emissions amount	Mt-CO_2

(1) Only time-related parameter equations, which contain the variables PGR, UPGR, PCDIUH, PCDIRH, EIUH, EIRH, PREGR, PC and PP. PGR showed logarithm trend as observed in the historical data from 2000 to 2014 and can be simulated by Equation (12). Variables UPGR, PCDIRH, PCDIUH, PREGR, EIRH, EIUH and PP exhibited quadratic polynomial trends and can be simulated by Equations (13)–(19), respectively. PC showed quartic polynomial trends and can be simulated by Equation (20).

$$\text{PGR} = -1.066\ln(t) + 7.5854 \quad (12)$$

$$\text{UPGR} = 0.0036t^2 - 0.2065t + 5.0061 \quad (13)$$

$$\text{PCDIRH} = 20.423t^2 - 48.467t + 2744.8 \quad (14)$$

$$\text{PCDIUH} = 25.183t^2 + 448.84t + 6989.3 \quad (15)$$

$$\text{PREGR} = 0.0179t^2 + 0.1573t + 3.304 \quad (16)$$

$$\text{EIRH} = -0.0008t^2 + 0.0149t + 0.1834 \quad (17)$$

$$\text{EIUH} = 0.00005t^2 - 0.0043t + 0.1431 \quad (18)$$

$$\text{PP} = 0.02.1t^2 + 0.8683t + 23.321 \quad (19)$$

$$\text{PC} = -0.0004t^4 + 0.027t^3 - 0.5174t^2 + 0.8269t + 69.792 \quad (20)$$

where t is time, with the year 2000 as the base, that is, t = 1 in 2000.

(2) The level equations, which contain the variables P, UP and PRE. The level variables are expressed in Table 3 using INTEG function.

$$\text{LEVEL}_\text{K} = \text{LEVEL}_\text{J} + (\text{INFLOW} - \text{OUTFLOW}) \times \text{DT} \quad (21)$$

where LEVEL is the level variable, INFLOW is the input rate, OUTFLOW is the output rate, and DT is the time interval from J moment in the past to the present time K:

$$\text{P} = \text{INTEG(PG, P initial value)} \quad (22)$$

$$\text{UP} = \text{INTEG(UPG, UP initial value)} \quad (23)$$

$$\text{PRE} = \text{INTEG(PREG, PRE initial value)} \quad (24)$$

(3) Other auxiliary equations expressed in model are defined as follows.

$$\text{PG} = \text{P} \times \text{PGR} \quad (25)$$

$$\text{UPG} = \text{UP} \times \text{UR} \quad (26)$$

$$\text{PREG} = \text{PRE} \times \text{PREGR} \quad (27)$$

$$\text{PUP} = \text{UP}/\text{P} \times 100 \quad (28)$$

$$\text{RP} = \text{UP}/\text{PUP} \times 100 - \text{UP} \quad (29)$$

$$\text{DIUH} = \text{PCDIUH} \times \text{UP} \quad (30)$$

$$\text{DIRH} = \text{PCDIRH} \times \text{RP} \quad (31)$$

$$\text{TADI} = \text{DIUH} + \text{DIRH} \quad (32)$$

$$\text{ECUH} = \text{DIUH} \times \text{EIUH} \quad (33)$$

$$\text{ECRH} = \text{DIRH} \times \text{EIRH} \quad (34)$$

$$\text{TECA} = \text{ECUH} + \text{ECRH} \quad (35)$$

$$\text{REA} = \text{TECA} \times \text{PRE}/100 \quad (36)$$

$$\text{FEA} = \text{TECA} - \text{REA} \quad (37)$$

$$\text{CA} = \text{FEA} \times \text{PC}/100 \quad (38)$$

$$\text{PA} = \text{FEA} \times \text{PP}/100 \quad (39)$$

$$\text{PNG} = 100 - \text{PC} - \text{PP} \quad (40)$$

$$\text{NGA} = \text{FEA} \times \text{PNG}/100 \quad (41)$$

$$\text{CECC} = 0.7476 \times 44/12 \quad (42)$$

$$\text{CECBC} = \text{CA} \times \text{CECC} \tag{43}$$

$$\text{CECP} = 0.5825 \times 44/12 \tag{44}$$

$$\text{CECBP} = \text{PA} \times \text{CECP} \tag{45}$$

$$\text{CECNG} = 0.4435 \times 44/12 \tag{46}$$

$$\text{CECBNG} = \text{NGA} \times \text{CECNG} \tag{47}$$

$$\text{TCEA} = \text{CECBC} + \text{CECBP} + \text{CECBNG} \tag{48}$$

4.3.2. Scenario Design

The combination of LMDI methodology and SD models provides a scientific basis for designing scenarios of household CO_2 emissions. Differences among the five scenarios are listed in Table 3:

Table 3. Household CO_2 emission Scenarios.

Scenario	Year	Growth Rate of Population	Growth Rate of Urban Population	Disposable Income of Urban Households	Disposable Income of Rural Households	Growth Rate of the Share of Non-Fossil Energy	Energy Intensity of Urban Households	Energy Intensity of Rural Households
		‰	%	Ten Thousand Yuan	Ten Thousand Yuan	%	Mtce/Billion Yuan	Mtce/Billion Yuan
BS	2015	3.51	3.13	2.06	0.72	7.55	8.29	21.7
	2016	4.19	2.72	2.19	0.78	7.19	8	20.55
	2017	4.06	2.65	2.32	0.85	7.03	7.73	19.24
	2018	3.94	2.58	2.46	0.92	6.87	7.46	17.77
	2019	3.81	2.52	2.6	0.99	6.71	7.21	16.14
	2020	3.69	2.46	2.75	1.07	6.55	6.96	14.35
PS	2015	6.26	2.17	2.1	0.7	7.59	8.33	21.55
	2016	6.26	2.17	2.26	0.75	7.59	7.96	20.60
	2017	6.26	2.17	2.42	0.79	7.59	7.61	19.69
	2018	6.26	2.17	2.6	0.83	7.59	7.27	18.82
	2019	6.26	2.17	2.79	0.87	7.59	6.95	17.99
	2020	6.26	2.17	3	0.92	7.59	6.65	17.19
AS-1	2015	3.51	3.29	2.06	0.72	7.55	8.29	21.7
	2016	4.19	3.29	2.19	0.78	7.19	8	20.55
	2017	4.06	3.29	2.32	0.85	7.03	7.73	19.24
	2018	3.94	3.29	2.46	0.92	6.87	7.46	17.77
	2019	3.81	3.29	2.6	0.99	6.71	7.21	16.14
	2020	3.69	3.29	2.75	1.07	6.55	6.96	14.35
AS-2	2015	3.51	3.29	2.06	0.72	12.87	8.29	21.7
	2016	4.19	3.29	2.19	0.78	12.87	8	20.55
	2017	4.06	3.29	2.32	0.85	12.87	7.73	19.24
	2018	3.94	3.29	2.46	0.92	12.87	7.46	17.77
	2019	3.81	3.29	2.6	0.99	12.87	7.21	16.14
	2020	3.69	3.29	2.75	1.07	12.87	6.96	14.35
AS-3	2015	3.51	3.29	2.06	0.72	12.87	8.19	21.18
	2016	4.19	3.29	2.19	0.78	12.87	7.69	19.91
	2017	4.06	3.29	2.32	0.85	12.87	7.23	18.71
	2018	3.94	3.29	2.46	0.92	12.87	6.79	17.58
	2019	3.81	3.29	2.6	0.99	12.87	6.38	16.52
	2020	3.69	3.29	2.75	1.07	12.87	6.00	15.52

(1) Baseline scenario (BS): The growth rate of population, growth rate of urban population, per capita disposable income, energy intensity, energy mix, and growth rate of non-fossil energy will evolve through the smooth trend of the period 2000–2014, which is extrapolated to 2015–2020 using the geometric growth rate method.

(2) Plan scenario (PS): PS is a current policy scenario that is a frame of reference. The content of the "13th Five-year Plan" (from 2016 to 2020) mentioned that the Chinese government will enhance energy-saving and CO_2 emission reduction efforts. In 2020, the total population is assumed to be 14.2 billion persons, which follows an annual growth rate of 6.26‰; the urbanization rate reaches 60%; the population of urban households will increase to 8.52 billion persons at an annual growth rate of 2.17%; per capita disposable income of urban and rural households will be approximately double that in 2010; the energy intensity of urban and rural households will gradually drop to 6.65 and 17.19 Mtce/billion yuan respectively; and the proportion of total energy consumption accounted for by non-fossil energy will be 15%, following an annual growth rate of 6.42%.

(3) Adjustment scenario 1 (AS-1): Scenario AS-1 is an adjustment scenario by improving the urbanization rate. The proportion of population accounted for by urban population will increase from 54.77% in 2014 to 65% in 2020, and the amount of urban population will increase to 9.1 billion persons in 2020, which follows an annual growth rate of 3.29%. The rest of the variables will evolve as in the BS.

(4) Adjustment scenario 2 (AS-2): Scenario AS-2 is an adjustment scenario by increasing the applications of non-fossil energy sources. The proportion of total energy consumption accounted for by non-fossil energy will increase from 9.67% in 2014 to 20% in 2020, which follows an annual growth rate of 12.87%. The rest of the variables will evolve as in scenario AS-1.

(5) Adjustment scenario 3 (AS-3): Scenario AS-3 is an adjustment scenario by reducing the energy intensity. The energy intensity of urban and rural households will gradually drop to 6 and 15.52 Mtce/billion yuan in 2020 respectively. The rest of the variables will evolve as in scenario AS-2.

4.3.3. Model Testing and Validation

The proposed SD model has been simulated, and the result is compared with the historical real data for total energy consumption and CO_2 emission (Table 4). The errors of energy consumption and CO_2 emissions are less than 2%, the simulated results show good conformity with historical trends. In addition, the results show their fitting degree is more than 0.94 and the model meets the simulation requirements.

Table 4. Simulated data versus historical data.

Year	Energy Consumption			CO_2 Emissions		
	Real Data (Mtce)	Simulated Data (Mtce)	Error (%)	Real Data (Mt-CO_2)	Simulated Data (Mt-CO_2)	Error (%)
2000	92.02	92.02	0.00	225.84	225.84	0.00
2001	93.03	92.24	0.84	224.64	223.64	0.45
2002	98.17	97.45	0.74	236.34	234.32	0.86
2003	111.51	110.81	0.63	269.13	266.73	0.89
2004	129.11	128.44	0.51	307.64	306.16	0.48
2005	133.62	133.00	0.47	314.82	313.84	0.31
2006	141.49	140.83	0.46	328.36	326.53	0.56
2007	151.18	150.42	0.51	341.30	339.73	0.46
2008	153.51	152.96	0.36	339.03	338.82	0.06
2009	160.06	159.51	0.34	350.12	347.96	0.62
2010	171.71	171.13	0.34	368.68	365.74	0.80
2011	184.71	184.19	0.28	394.46	389.66	1.22
2012	191.95	191.42	0.27	398.22	398.01	0.05
2013	209.13	208.62	0.24	430.52	425.41	1.19
2014	221.47	220.93	0.25	448.36	444.03	0.97

Error = absolute value of (((simulated data − real data)/real data) × 100).

4.3.4. Result of Scenarios

Different simulations based on the abovementioned scenario settings can be obtained by adjusting the parameters in the proposed SD model. The simulated household energy consumption and CO_2 emissions are shown in Figures 8 and 9 from 2015 to 2020:

(1) Figure 10 shows that China's household energy consumption may continuously increase from 221.47 Mtce in 2014 to 248.16 Mtce in 2020 (a 12.33% increase) if new policies for CO_2 emission reduction are not implemented after 2014 under BS. PS presents the largest increase in energy consumption among five scenarios because the growth rate of population was higher than in the other four scenarios. The household energy consumption in 2020 will be 259.16 Mtce in PS, which is more than 4.43% of the value in BS. However, the trend of energy consumption for AS-1 and AS-2 are close to that for BS. The household energy consumption in 2020 will be 249.65 Mtce both in AS-1 and AS-2, which are 1.849 Mtce more than that in BS. The energy consumptions in AS-3 will reach 231.49 Mtce in 2020,

which is less than 6.72% of the value in BS after taking further enhanced energy-saving measures to reduce energy intensity.

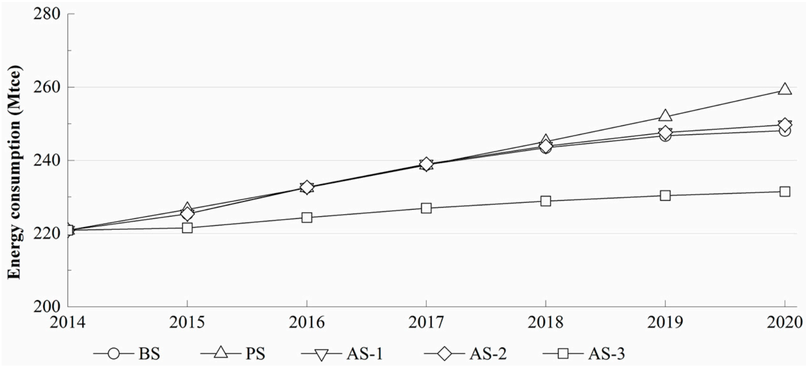

Figure 10. Household energy consumption scenario simulation.

Household energy consumption maintains an increasing trend in all five scenarios in the simulated period. The increase in income and growth of population lead to a rapid growth in the demand for home appliances and private car ownership, which increased the household energy consumption.

(2) Figure 11 shows that household CO_2 emissions in BS may increase from 444.03 Mt-CO_2 in 2014 to 466.8 Mt-CO_2 in 2020 (a 5.13% increase). Similar to the household energy consumption, the PS presents the largest increase in CO_2 emissions among the five scenarios. The CO_2 emissions in 2020 will be 475.65 Mt-CO_2 in PS, which is more than 1.9% of the value in BS. The household CO_2 emissions in 2020 in AS-1 is 2.8 Mt-CO_2 more than that in BS, which reveals that simply raising the rate of urbanization cannot reduce CO_2 emissions. The household energy consumptions increase in AS-2 and AS-3; the CO_2 emissions present a trend of decrease in AS-2 and AS-3 after promoting the proportion of energy accounted for by non-fossil energy and reducing energy intensity. The household CO_2 emissions in 2020 will be 435.98 Mt-CO_2 and 404.26 Mt-CO_2 in AS-2 and AS-3 respectively, which are less than 6.6% and 13.4% of the value in BS.

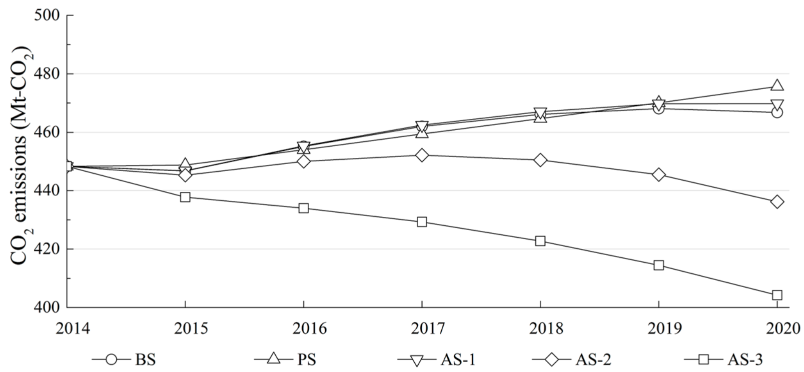

Figure 11. Household CO_2 emissions scenario simulation.

Thus, the household CO_2 emissions under "13th Five-year Plan" will maintain an increasing trend, which contradicts the target of CO_2 emission reduction. However, the household CO_2 emissions may be inhibited by reducing energy intensity and developing non-fossil energy, such as improving the infrastructure of natural gas supply and the incentives to buy fuel-efficient vehicles and energy-efficient electronic products, as well as promoting solar power utilization [10].

5. Conclusions

(1) An integrated model based on LMDI methodology and SD model is formulated in this study. The errors of the main variables are less than 2%, which indicates that the integrated model performs well in calculating the contribution of the different influencing factors on household CO_2 emissions and analyzing the options for CO_2 emission mitigation.

(2) The simulations indicate that in the case of "13th Five-year Plan", household CO_2 emissions in China will maintain an increasing trend, and reach 475.65 Mt-CO_2 in 2020, which is more than 6.09% of the value in 2014. By decreasing energy intensity, such as by improving the infrastructure of natural gas supply and incentives to buy fuel-efficient vehicles and energy-efficient electronic products, CO_2 emissions will decrease to 404.26 Mt-CO_2 in 2020, which is 9.84% lower than the emissions in 2014.

(3) The consideration of household energy mix, which prioritizes coal, has changed significantly, the reduction potential by developing non-fossil energy sources is limited. The simulation shows that the proportion of total energy consumption accounted for by non-fossil energy increases from 9.67% in 2014 to 20% in 2020, but the total CO_2 emissions amount only decreases by 2.67% from 2014 to 2020.

(4) Although the urbanization improvement makes household CO_2 emissions decrease, raising the rate of urbanization cannot reduce the household CO_2 emissions under the comprehensive influence of other factors. On the contrary, when the proportion of population accounted for by urban population increases to 65% in 2020, the total CO_2 emissions amount increased by 4.74% from 2014 to 2020.

This study builds an integrated model to reveals the options for reducing household CO_2 emissions in China. In our future research, we would further improve the model and expand its application scope based on the present study, providing a more specific basis for policy-makers to develop emission-reduction policies.

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