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Toward carbon free by 2060: A decarbonization roadmap of operational residential buildings in China

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A B S T R A C T
Restraining the rapid growth of operational carbon emissions from residential buildings is critical to achieve carbon neutrality. To illustrate the future decarbonization roadmap, this study builds an end-use emissions model to analyze past decarbonization efforts and projected emission change in China’s residential building operations by mid-century. From 2001 to 2018, residential building operations reduced emissions by 2.77 (±1.61) giga tons of carbon dioxide (GtCO₂). Dynamic simulation results of the emission model reveal that residential building operations will peak in 2031 (±3) with 0.95 (±0.06) GtCO₂. Energy-related carbon intensity (~44%) and energy intensity (~36%) are identified as the primary factors affecting carbon peak status, with heating (~87%) playing a crucial role in energy intensity. A feasible emission path towards carbon neutrality suggests limiting urban and rural residential building emissions to 0.38 and 0.27 GtCO₂ in 2030, respectively, and offsetting only 0.03 and 0.01 GtCO₂ in urban and rural regions by 2060, to become carbon free. Overall, the study proposes a stepwise data analysis benchmark to decarbonize the residential building operations of top emitters, contributing to global building decarbonization in the era of carbon neutrality.

1. Introduction

The building sector is responsible for over 37% of energy-related carbon dioxide (CO₂) emissions globally and consumes more than a third of the world’s final energy. Despite this, the sector’s energy demand is increasing as floor space expands rapidly across the globe [1]. Moreover, the high demand for energy in the building sector is expected to persist in the upcoming decades, fueled by population and economic growth [2,3]. As of 2020, residential buildings already accounted for 22% of energy use across all sectors and are projected to generate over 50% of CO₂ emissions from building operations globally in the near-zero scenario from 2010 to 2030 [4]. China, with its vast largest population and strong economic growth, is experiencing a rapid increase in energy demand for residential buildings; furthermore, its energy consumption and carbon emissions have long been the highest of all countries [5,6]. Since 2016, carbon emissions from urban residential building operations in China have been increasing at an average annual rate of 3.4%, while those from rural areas have remained relatively stable [7,8].

In addition, residential buildings present enormous potential for cost-effective decarbonization [9], with end-use energy savings offering excellent feasibility of technology and measures [10], driven by existing energy-saving and emission reduction policies. The energy consumption of residential building operations is directly linked to end-use activity, and changes in demand and efficiency will inevitably impact emissions [11]. A study by Fan, Yu [12] demonstrated that heating and cooling contributed the most to carbon emissions in urban residential buildings between 1996 and 2012, accounting for 40% of emissions, followed by cooking and water heating at 30%. However, while the study took a bottom-up approach to assess the contribution of end-uses to residential decarbonization, it used static scenario models and failed to account for uncertainty in emission model parameters. Moreover, current studies assessing past and future carbon emissions often overlook end-use activities. Based on the status quo, three questions are raised for China’s residential buildings:

• How is the mitigation strength determined by reviewing past residential building emissions?
• What are the possible paths of future carbon emissions from residential building operations?

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Abbreviations

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<th>Abbreviation</th>
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<tbody>
<tr>
<td>BAU</td>
<td>Business as usual</td>
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<tr>
<td>EKC</td>
<td>Environmental Kuznets curve</td>
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<tr>
<td>GDP</td>
<td>Gross domestic product</td>
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<tr>
<td>GtCO₂</td>
<td>Giga tons of standard coal equivalent</td>
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<tr>
<td>IPAT</td>
<td>Impact on population, affluence, and technology</td>
</tr>
<tr>
<td>kgce</td>
<td>Kilograms of standard coal equivalent</td>
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<tr>
<td>KgCO₂</td>
<td>Kilograms of carbon dioxide</td>
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<tr>
<td>Mtce</td>
<td>Mega tons of standard coal equivalent</td>
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<td>MtCO₂</td>
<td>Mega tons of carbon dioxide</td>
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<td>SD</td>
<td>Standard deviation</td>
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Symbols

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<th>Symbol</th>
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<tbody>
<tr>
<td>Cᵢ</td>
<td>Carbon emissions of residential buildings</td>
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<tr>
<td>Cᵢᵣ</td>
<td>Carbon emission of rural residential buildings</td>
</tr>
<tr>
<td>Cᵢᵤ</td>
<td>Carbon emission of urban residential buildings</td>
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<tr>
<td>ΔCᵢᵣ</td>
<td>Contribution of factor i to Cᵢᵣ</td>
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2. Literature review

Global warming can be mitigated to prevent major catastrophes through deep decarbonization, which requires cross-cutting research [13]. Torchio, Lucia [14] assessed the decarbonization performance of various countries from social and economic perspectives based on the Human Development Index and Gross Domestic Product (GDP) indices. Grisolia, Lucia [15] investigated the impact of technological proficiency on decarbonization using the Education Index. To aid in decarbonization, the Thermodynamic Human Development Index has been proposed [16,17] and improved to analyze the optimized utilization of third-generation biofuels [18]. In addition, Langevin, Harris [19] found that utilizing fuel conversion, envelope, and control measures to achieve decarbonization in power generation was a highly cost-effective approach. Besides, Langevin, Harris [19] investigated decarbonization technologies that aim to enhance building energy efficiency and flexibility by reducing the demand for fossil fuels.

Assessing past decarbonization efforts is critical in determining a country’s potential for reducing emissions [21]. The choice of an appropriate method for this assessment is therefore essential. As a classical index decomposition analysis, LMDI has been extensively applied in the fields of energy economy [22,23] and ecological environment [24,25] to evaluate the impact of corresponding driving factors on research objectives. Several scholars have also adopted this decomposition method to study carbon emissions and energy intensity in the building sector. For example, He, Yue [26] identified five factors that influenced carbon emissions in China’s building sector during 2000–2015 and quantified their contribution to emissions using the LMDI method. Zhong, Hu [27] used the LMDI method to assess the energy-saving capabilities of residential and commercial buildings from 1971 to 2060. Given the widespread use of the LMDI method in estimating the factors that influence building emissions and energy targets, this method will be adopted in this study [28,29].

Currently, there are two main methods utilized by scholars for analyzing emissions peaks: Environmental Kuznets Curve (EKC) and the scenario analysis. Fang, Li [30] verified the hypothesis of the EKC relationship between various industrial sectors and GDP per capita. It was discovered that industrial buildings conformed to the EKC curve, and the GDP per capita in 2017 had not reached half of the turning point value, which means that there is still a long time before peak emissions are reached in China’s industrial buildings. While the EKC method provides a simple and effective way to assess peak emissions through economic indicators, it falls short in obtaining the exact peaking time.
and representing emissions over a long time series [31]. To address this limitation, scholars have turned to the scenario analysis. For instance, Tang, Guo [32] investigated the low carbonization path of China’s building sector under 2°C and 1.5°C scenarios, revealing that to achieve the targets, cumulative CO₂ emissions in China’s building sector should be suppressed to 153.8 giga tons (Gt) and 86.5 Gt, respectively. Hou, Feng [33] studied the impact of climate measures on carbon emissions in China’s building sector, creating three scenarios of business as usual, strong policy intervention, and peaking-target contingent policy. However, the above scenario analysis was static and did not consider the uncertainty of the emission model parameters. Therefore, the future carbon emission path analysis would benefit from the application of dynamic scenario analysis. Recently, dynamic scenario analysis has appeared in building sector studies. For example, Zhang, Ma [34] formed a dynamic scenario model and presented a dynamic emission roadmap of China’s commercial buildings. According to their results, emissions from China’s commercial buildings would peak in 2039 (±5) at 1.37 (±0.26) GtCO₂.

In general, scholars have used either top-down or bottom-up emission models to account for and forecast carbon emissions. The top-down emission model based on the EKC is a classic method used to identify the relationship between macroeconomic factors (e.g., GDP per capita) and emissions to determine emissions status [35]. However, this macro nature of the forecast data makes it challenging to obtain detailed information for developing targeted decarbonization strategies. On the other hand, the bottom-up emission model is more amenable to this type of analysis [36]. For example, Zhao, Yu [37] proposed a bottom-up model to demonstrate carbon emissions and energy consumption at the national and industry levels under the 2°C target. Yang, Pan [38] established a bottom-up emission model by considering end-use activity, and their results suggested that carbon emissions in China’s building sector should be limited to 2.53 GtCO₂ and 2.42 GtCO₂ in 2030 and 2050, respectively. Likewise, these emission models are all static and cannot account for uncertainty in emission parameters, highlighting the need for dynamic scenario analysis. Despite this need, dynamic scenario analysis remains uncommon in China’s urban and rural residential building operations. Based on the review above, the following two points should be noted when calculating carbon emissions and analyzing future emission peaks:

For dynamic emission models applied in China’s urban and rural residential buildings, the application of end-use emission models combined with dynamic simulation has rarely been proposed in existing studies. This failure to account for the uncertainties in emissions from energy changes in each end-use activity can lead to a loss of targeted policy-making references, which limits the development of decarbonization strategies. Hence, it is necessary to build a bottom-up model considering end-use activity and use dynamic simulations to account for uncertainties.

For the benchmarks of emissions in China’s urban and rural residential buildings, to address the current difficult situation of deep decarbonization, achieving carbon neutrality by 2060 will require strong policy intervention. However, a key question is how to reach this goal step-by-step. Answering this question requires phased emission benchmarks as guidance.

To achieve carbon neutrality, a dynamic emission model for China’s residential building must consider the uncertainties of various indicators. Therefore, this study attempts to establish a bottom-up dynamic emission model and develop emission paths for China’s urban and rural residential building operations from 2000 to 2060. The contributions of this study are as follows:

Uncertainty caused by the change in end-use activity is considered in emissions simulations. Some studies used bottom-up static emission models to project future emission paths. However, these models have not considered the uncertainty of end-use energy intensity and other emission parameters, which can affect carbon peaking. Therefore, this study emphasizes a dynamic scenario analysis of urban and rural residential buildings in China with a bottom-up perspective. This is achieved through the application of impact on population, affluence, and technology (IPAT), and by considering end-use activity, building an end-use emission model, and combining Monte Carlo simulations to construct a dynamic carbon emissions roadmap for 2000–2060.

Phased emission benchmarks are proposed to guide steps toward carbon neutrality in the future. The bottom-up emission model is used for dynamic simulation to identify the end-use energy benchmarks of urban and rural residential buildings, and the contribution of each end-use to emissions. To achieve carbon neutrality, emission benchmarks and projected carbon emission parameters at key years are determined to achieve carbon neutral targets by 2060. Finally, a series of decarbonization strategies are recommended based on the analysis of emissions and energy status.

3. Materials and methods

This section outlines the process of establishing a model that evaluates past decarbonization under different scenarios while simulating future carbon emissions in Chinese residential building operations. Section 3.1 presents the development of the end-use emission model, while Section 3.2 introduces decarbonization progress from 2001 to 2018. Section 3.3 describes the dynamic scenario analysis of the prospective carbon emission path. Additionally, Section 3.4 provides an explanation of the data used in this study.

3.1. Residential building emission model

To assess the past and future carbon emission levels of residential building operations in China, this study extended the IPAT model by quantifying the contribution and impact of various emissions-related factors [39] An emission model was then established to present the carbon emission path. The IPAT model is a well-known equation used to measure human impact on environmental pressure [40], and is widely used in fields such as energy, economy, and environment. It is shown as follows:

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

(1)

where I, P, A, and T refer to the human impact, population size, affluence, and technological level of the area being calculated, respectively.

When applying the IPAT model to carbon emission calculations, carbon emissions are considered human impacts in Eq. (1), while population size [41] represents the corresponding regional population. For affluence and technological level, most scholars utilized social and economic status indicators, energy intensity [42], and energy-related carbon intensity [43] (i.e., emission factors) to measure. For instance, the Kaya identity based on the IPAT model [44,45] has been extensively used by scholars to calculate carbon emissions, energy consumption, and energy savings. Nevertheless, social and economic indicators [46] have many unpredictable influencing factors, which can affect the reliability of the emission model [47]. To eliminate the influence of social and economic factors on past and future carbon emission results, recent research and application by Yan, Xiang [48] utilized the amount of floor space per person [49] as a measure of affluence. To evaluate the carbon emission China’s residential building operations, this study constructed a carbon emission model that calculates the carbon emission of residential buildings in China (Cr), as well as the carbon emission of China’s urban residential buildings (Cr,u) and rural residential buildings (Cr,r). The model includes many factors that represent the emissions characteristics of residential building emissions, specifically the population (P), per capita floor space (f), energy intensity (e) and energy-related carbon intensity (ef), as shown in Eqs. (2)–(4), Fig. 1, and Table 1.
The parameters in Eqs. (3) and (4) above form the basis for assessing past decarbonization and establishing dynamic emission models for different scenarios. In addition, technological development level plays an irreplaceable role in influencing carbon emissions [50], as energy intensity indicators used to assess the technological level are generally assumed to derive from six end-use activities: heating, appliances, cooking, hot water, cooling, and lighting [51,52]. Furthermore, since carbon emissions from China’s residential building operations primarily result from energy consumption in end-use activity [53], this study considered the demand and efficiency of each end-use as contributing factors to the energy intensity [54,55]. This enabled the determination of the energy intensity of each end-use and the development of an end-use carbon emissions model for China’s urban and rural residential building operations [56]. Then, Eqs. (3) and (4) can be extended as follows:

\[ C_{r, u} = P \cdot U \cdot f_{u, r} \cdot \sum_y C_{r, y} \cdot K_{r, u} \]  
\[ C_{r, c} = P \cdot (1 - U) \cdot f_{c, r} \cdot \sum_y C_{r, y} \cdot K_{r, c} \]  
\[ C_r = C_{r, u} + C_{r, c} \]  
(6)
(7)
(8)

where \( f_{u, r} \) and \( f_{c, r} \) denote urban and rural end-use factors, respectively; \( K_{r, u} \) and \( K_{r, c} \) represent the energy intensity of heating end use in urban and rural buildings, respectively; \( C_r \) denotes end-use carbon emissions; \( P \) is the population size; \( U \) is the urbanization level; \( f_{u, r} \) and \( f_{c, r} \) denote the floor space per capita of urban and rural residential buildings, respectively; \( C_{r, y} \) is the energy intensity of residential building operations in China (ER); \( C_{r, u} \) and \( C_{r, c} \) are the carbon emissions of urban and rural residential buildings, respectively; \( C_r \) is the total carbon emissions; \( K_{r, u} \) and \( K_{r, c} \) represent the energy intensity of heating end use in urban and rural buildings, respectively.

In the establishment of emission models, the primary focus is not on their ability to accurately reflect the current economic and technological level [57] but rather on their ability to capture the trend of emissions development [58]. Among all the influencing factors in the equation, energy intensity in each end-use has greater control significance than economic level and population; hence, the contribution of energy intensity to carbon emissions in end-use activities is essential in formulating strategies and measures to control energy consumption and reduce carbon emissions [59].

### 3.2. Past decarbonization assessment

Based on the above emission model, the LMDI method was used to assess the contribution of each factor in the emission model to carbon emissions [60,61] and evaluate past decarbonization. This method analyzes the impact of each parameter on the equation’s outcome and has been widely applied in emission reductions assessments [62] to study and explore decarbonization in China’s residential building operations. Thus, by combining the emission model equations (see Eqs. (3) and (4)) with the LMDI decomposition method, the change in emissions during period \( \Delta T \) (\( \Delta C_{r, t} \)) can be expressed as follows:

\[ \Delta C_{r, t} = C_{r, t} - C_{r, 0} = (\Delta C_{r, f} + \Delta C_{r, d} + \Delta C_{r, f} + \Delta C_{r, e} + \Delta C_{r, r})_{t} \]  
\[ \Delta C_{r, t} = \frac{C_{r, t} - C_{r, 0}}{\ln C_{r, t} - \ln C_{r, 0}} \cdot \ln \left( \frac{P_{t}^{\text{in}}}{P_{0}^{\text{in}}} \right) \]  
(9)
(10)

Therefore, the equation to express the carbon emission reductions of residential building operations in China (ER_{r, t}) is:

\[ \text{ER}_{r, t} = - \sum \Delta C_{r, t} \]  
(11)

where \( \Delta C_{r, t} \) is the change in carbon emissions during period \( \Delta T \).

The contribution of each emission-related impact factor was evaluated by the LMDI decomposition method, and past carbon emissions in residential buildings were decomposed. It was found that the increase in rural population appears to be the main contributor to rural decarbonization, with a large value; however, this finding does not align with the actual situation of China’s rural residential building decarbonization, and thus, it is considered a false contribution [63]. This result could potentially mislead decision makers. Therefore, it is crucial to note that urban and rural building decarbonization cannot be calculated separately.

### 3.3. Future emission simulation

This section focuses on establishing future carbon emission scenarios using different scenario analyses to form a dynamic carbon emission roadmap. Analysis of different emission scenarios is frequently used to illustrate future carbon emission paths [64]. To establish different emission scenarios, several factors contributing to carbon emissions were selected and the corresponding feedback and variation were
reflected in the carbon emissions as these selected factors changed \[65\]. Furthermore, Eq. (8) indicates that the sum of the variation range of the energy intensity for each end use should be consistent with the variation range of the total energy intensity. Hence, the static emission scenario for two types of residential buildings can be obtained from Eqs. (6) and (7), and this scenario was defined as the emission scenario in a business-as-usual (BAU) state. Since the carbon emission path under the BAU scenario has the highest probability of occurrence among all possible scenarios, the development of carbon emissions in the period 2000–2060 under this scenario was considered. Additionally, other possible emission scenarios could be designed as the BAU scenario of static emissions \[66\].

Using the emission model proposed in Section 3.1, a static emission scenario was calculated from 2000 to 2060. Then, a dynamic emission scenario was developed through Monte Carlo simulation \[67\]. Dynamic simulation mainly depends on varying probabilities of each parameter in the static emission model, indicating the range \[68\] of future carbon emissions and energy demand. Monte Carlo simulation can calculate the uncertainty range (see Eq. (13)) based on a determined random value \([\omega]\), which is widely used in risk management. To control the variation in future carbon emissions, the random value \((\omega)\) of parameters in the emission model was determined according to a certain distribution, and the carbon emission paths of multiple scenarios were generated. In this study, a 100,000-run simulation was adopted to ensure the reliability of the simulation results. Ultimately, the simulation results were fitted to obtain the carbon emissions and corresponding peaking time under different probabilities. The number of simulations can affect the results, but the results were found to be reliable even as the number increased.

\[
C_{\text{Dynamic}} = C_{\text{Static}} \cdot \left(1 + \omega \cdot \frac{T - 2018}{2060 - 2018}\right), \quad \omega \sim N(0, \sigma^2) \quad (13)
\]

This section focuses on dynamic simulation, which provided a range of possible carbon peak and corresponding peaking time in different scenarios for China’s residential building operation in the future. These simulation results can be a helpful reference for setting decarbonization targets and taking necessary actions.

3.4. Dataset

In this study, data for the period 2000–2060 on energy intensity, floor space, and energy-related carbon intensity in China’s residential building operations were collected from CBED (www.cbed.cn). Past and projected population and urbanization rates were obtained from the United Nations website (un.org/development/desa/pd/data/landing-page). Moreover, the definition of random values for parameter changes in dynamic simulation is presented in Table B1 (see Appendix B).

4. Results

4.1. Past decarbonization of residential building operations

Based on the evaluation of Eqs. 9-12, the decarbonization of China’s residential building operations from 2001 to 2018 is presented in Fig. 2, including error bands to consider the uncertainty of the decarbonization result at different measurements. The error values for the decarbonization of residential building operations were \(-89\) mega tons of \(\text{CO}_2\) (Mt\(\text{CO}_2\)) per year for total reduction, \(\pm63\) kg\(\text{CO}_2\) for \(\text{CO}_2\) reduction per capita, and \(\pm1.5\) kg\(\text{ce}\) per m\(^2\) for \(\text{CO}_2\) reduction per floor space.

Generally, the decarbonization of residential building operations in China has been evaluated for the period 2001–2018, with a total value of 2.77 (±1.61) Mt\(\text{CO}_2\) (see Fig. 2 a). The decarbonization curves exhibited a fluctuating pattern, resembling an “M + M” shape, indicating that decarbonization was not monotonous and consistent on a yearly basis. Specifically, the past decarbonization was divided into four periods, each with a corresponding \(\text{CO}_2\) reduction value for residential building operations: 296 (±446, 2001–2005), 636 (±446, 2006–2010), 929 (±446, 2011–2015) and 912 (±268, 2016–2018) Mt\(\text{CO}_2\). Fig. 2 b indicates the variations in decarbonization curves per capita and per floor space in the residential building operation stage, which are consistent with the corresponding \(\text{CO}_2\) reduction curve. Furthermore, the decarbonization intensity per floor space for China’s residential building operations was 1.7 (±1.5, 2001–2005), 3.2 (±1.5, 2006–2010), 4.0 (±1.5, 2011–2015), and 5.6 (±1.5, 2016–2018) kg\(\text{ce}\) m\(^{-2}\) year\(^{-1}\) across the four stages. By fitting the decarbonization curves of different measurements, it can be clearly observed that these curves continuously increased, with the accumulated decarbonization value growing steadily at a yearly rate of 16 Mt\(\text{CO}_2\). In short, a past assessment of decarbonization of residential building operations in China is required to address Question 1 of Section 1.

4.2. Future carbon emission paths of residential building operations

Fig. 3 shows the carbon emission paths and dynamic emission simulation scenarios with different probabilities for residential building operations from 2000 to 2060, and the blue area with progressive shades represents the error bands. It can be observed that the brown and yellow curves of both urban and rural regions form inverted U-shaped curve, representing the static emission path of past and future residential building operations. This static carbon emission path reveals that carbon emissions from the residential building operation stage in urban and rural areas will peak in 2035 at 0.56 Gt\(\text{CO}_2\) and 2025 at 0.40 Gt\(\text{CO}_2\), respectively. The dynamic simulation paths, however, show different peaking time for the future simulation paths based on different probabilities, as shown in Fig. 3.

This study employed Monte Carlo data simulation, running 100,000 times and considering uncertainties to determine the most likely peaking time for carbon emissions and energy demand in China’s residential building operations. The standard deviation (SD) index was used to reflect errors caused by simulation uncertainty, as shown in Fig. 4. Specifically, based on the simulation data with an uncertainty of 3 years, China’s carbon emissions in the residential building operation stage will peak in 2031, which is conveniently expressed as 2031 (±3) here. Fig. 4 a shows that the carbon peaking time for urban residential building operations is estimated to be 2035 (±4), while rural regions are expected to peak in 2026 (±4). The total energy demand for residential building operations in China is predicted to peak in 2036 (±3), with urban and rural areas reaching their respective peaks in 2042 (±6) and 2028 (±4). Overall, it can be observed that controlling urban carbon emissions is the most vital factor in achieving an earlier peak in China’s carbon emissions, as both \(\text{CO}_2\) emissions and energy demand tend to peak much later in rural regions than in urban regions. Furthermore, according to the above data, the peaking time of energy demand was generally later than peaking time that of carbon emissions for both regions.

Based on the dynamic simulation presented above, it can be calculated that the total carbon emissions and energy demand in residential building operations will peak at 0.95 (±0.06) Gt\(\text{CO}_2\) and 0.69 (±0.04) gigatons of standard coal equivalent (Gt\(\text{ce}\)), respectively. As shown in Fig. 5, the carbon peak and energy peak of urban residential building operations are projected to reach 0.57 (±0.06) Gt\(\text{CO}_2\) and 0.48 (±0.04) Gt\(\text{ce}\), respectively. Meanwhile, it can also be observed that the carbon peak in rural areas is 0.40 (±0.02) Gt\(\text{CO}_2\) and the corresponding energy demand peak is 0.23 (±0.01) Gt\(\text{ce}\). As mentioned earlier, it is noteworthy that the static peak (see Fig. 3) and the dynamic simulation data (see Figs. 4 and 5) agree within the error range.

The dynamic scenarios formed by Monte Carlo simulation, as shown in Figs. 4 and 5, have a certain degree of uncertainty in the peak value. For example, as illustrated in Fig. 3 b and 4 a, the carbon peak of rural residential building operations will reach its peak in 2025 under the

\[^3\] 1 kg coal equivalent corresponds to a value specified as 7000 kilocalories.
static scenario and 2026 under the dynamic scenario (due to an uncertainty exists in the dynamic scenario). Therefore, it is essential to discuss and analyze the uncertainties under dynamic scenarios. For this reason, sensitivity analysis of carbon emission model parameters to the uncertainties of the emissions peak and peaking time is presented in Figs. 6 and 7. The sensitivity analysis is performed separately for urban and rural residential building operations due to the difference in the carbon peak between them, in order to avoid the impact of urban and rural differences on the sensitivity results.

The sensitivity analysis of urban residential buildings presented in Fig. 6 indicates that the energy-related carbon intensity exerts the greatest influence on the uncertainty of the carbon peak, accounting for 44.3%. Following closely, energy intensity contributes to 35.7%. The combined sum of the uncertainty of these two indicators for the peak of carbon emissions accounts for 80.0% ($\pm 0.05$) GtCO$_2$, making it the major contributor to the uncertainty of the emissions peak. Compared
with the above two factors, other factors, including floor space per capita, population size and urbanization level, have a relatively small contribution, accounting for a total of 20.0%, which should not be disregarded. The right side of Fig. 6 shows the contribution levels of all factors to the peaking time of carbon emissions, which are very similar to left side. The analysis shows that the contribution of energy-related carbon intensity to the peaking time reaches a maximum of 44.3%, and the proportion of energy intensity is the second-highest at 35.7%.

The combined contribution of these two factors is the same as that of the figure on the left, reaching 80.0% ($\pm$3 years).

Fig. 7 shows the sensitivity contribution diagram of uncertainty in the dynamic scenario from rural residential building operations. The analysis reveals that the factors contributing most to the uncertainty of rural residential building emissions peak or peaking time are energy-related carbon intensity and energy intensity, consistent with the findings for urban regions. However, the relative importance of the last three
influencing factors changes varies for rural regions. For the uncertainty of the emissions peak in rural regions, floor space per capita plays a more important role than urbanization level. Importantly, the results emphasize energy-related carbon intensity and energy intensity are the primary determinants of the uncertainty in projected future carbon emission paths, while the contribution of other factors should be treated with caution.

Figs. 6 and 7 also illustrate that the contribution of energy intensity to the uncertainty of the emissions peak and peaking time is disaggregated into proportions for each end-use activity. As depicted in Fig. 6 a, the end-use activity of heating dominates the energy intensity sensitivity contribution to the uncertainty of CO$_2$ peak, accounting for 87.2%. Similarly, in terms of the energy intensity contribution to the uncertainty of peaking time in urban regions, the contribution of heating end-use activity is also the largest at 91.8%, while appliances, cooking, hot water, and cooling account for 4.1%, 2.0%, 2.0%, and 0.1%, respectively, which is similar to the contribution of CO$_2$ peak. As shown in Fig. 7, heating end-use activity also accounts for the vast majority of the energy intensity contribution to the uncertainty of CO$_2$ peak and peaking time in rural residential buildings. It is worth noting that in the sensitivity analysis of the rural CO$_2$ peak, the proportion of end-use activity of heating decreases to 84.2%, while the contribution of appliances increases to 10.5% compared to that in the urban peak. In summary, the above findings indicate that the heating end-use activity is a key factor in determining the uncertainty of energy intensity, and the impact of heating should be emphasized in the discussion of future decarbonization plans.

5. Discussion

5.1. Benchmarks of end-use energy consumption in residential building operations

Section 4 demonstrates that under the dynamic BAU scenario, the carbon emissions from urban and rural residential building operations will peak in 2035 at 0.57 (±0.06) GtCO$_2$ and 2026 at 0.40 (±0.02) GtCO$_2$, respectively. To determine the benchmarks for end-use energy consumption required to achieve an emissions peak, as well as the end-use activity with the greatest impact on the carbon peak, Section 5.1 proposes the correlation density between the peak of each end-use energy intensity and emissions peak, and end-use benchmarks are captured. The aim of this analysis is to explore the degree of correlation between changes in end-use energy intensity and emissions peak in urban and rural residential building operations.

According to the dynamic simulation results of emissions under the BAU scenario presented in Section 4.2, this section proposes end-use benchmarks for achieving carbon peaks in future residential building operations; the possible errors of these benchmarks were considered, and were reflected by the SD. As depicted in Figs. 8 and 9, the energy intensity of each end-use activity in urban and rural residential buildings is positively correlated with the carbon peak, indicating that limiting the energy consumption of each end-use activity is necessary to achieve an earlier carbon peak. Using the energy intensity peak of each end-use activity at peak carbon, six end-use energy consumption benchmarks were calculated. For urban residential building operations, the benchmark for appliance, cooking, cooling, heating, hot water, and lighting end-use activities to reach the emissions peak is 65 (±2) mega tons of standard coal equivalent (Mtce), 78 (±4) Mtce, 49 Mtce, 262 (±1) Mtce, 53 Mtce, and 35 Mtce, respectively. The energy consumption of the six end-use activities in rural residential building operations should be restrained below the benchmark of 41 (±2) Mtce, 36 (±2) Mtce, 35 (±2) Mtce, 151 (±16) Mtce, 35 Mtce, and 9 Mtce, respectively. As shown in Fig. 8, the correlation analysis of the six end-use activities in urban residential building operations reveals that appliance and heating end-use activities have the strongest correlation with the carbon emission peak, followed by cooking, cooling, hot water, and lighting end use activities. Similar results were found in rural residential building operations, but the heating end-use activity has the strongest correlation with the emission peak, with a correlation coefficient of 0.17, significantly higher than other end-uses, as shown in Fig. 9. In addition, it is more practical to prioritize the energy consumption level of each end-use activity, as limiting these activities can directly and efficiently reduce carbon emissions. In this regard, more stringent measures must be taken to reduce the energy consumption of heating and appliance end-use activities. Particularly, greater emphasis should be placed on reducing energy consumption in heating end-use activities from rural residential building operations. In summary, Sections 4.2 and 5.1 effectively addresses the Question 2 of Section 1.

5.2. Carbon neutral pathways of residential building operations

Section 5.1 captures each end-use energy consumption benchmark for urban and rural residential building operations under the dynamic BAU scenario. Moreover, this section proposes a decarbonization roadmap for China’s residential building operations towards carbon neutrality by analyzing the feasible decarbonization path under different emission scenarios. The roadmap is based on phased emission targets and relies on the government’s accurate and efficacious reduction strategy due to the high uncertainty regarding emissions development until 2060 [70]. As the focus is on the path towards carbon neutrality, the decarbonization roadmap only focuses on the future trend of carbon emissions and shows the suggested control targets and realistic possibilities to achieve the roadmap. This section provides a comprehensive answer to Question 3 of Section 1.

In this section, three carbon emissions paths are selected under SDs of $-\sigma$, $-2\sigma$, and $-3\sigma$ condition statuses, where the uncertainty of carbon emissions is measured by SD as described in Section 4.2. As shown in Fig. 10, the curves that approach the green dotted line, representing carbon neutrality, indicate that the more aggressive the decarbonization, the less likely the path will be achieved in the BAU scenario. The probability of future carbon emission paths occurring between the BAU scenario and $-\sigma$ scenario is 34.1%. Between the $-2\sigma$ and $-\sigma$ scenarios, the probability of carbon emission paths is 13.6%, while between the $-3\sigma$ and $-2\sigma$ scenarios, the probability drops to 2.1%, indicating that achieving this path is highly challenging.

In this section, a more feasible and realistic decarbonization roadmap for China’s residential building operations towards carbon neutrality is proposed. The roadmap is based on the idea of gradual
carbon emission reduction and is divided into three steps. First, ten control points (see Points A1–A5 and B1–B5 in Fig. 10) were selected in each decade on three different SD emission paths as a stage. These control points represent different years and emission data and are marked as control targets under three emission paths with different uncertainties: A1 (B1) on the curve in $-\sigma$ condition status in 2020, A2 (B2) on the curve in $-2\sigma$ condition status in 2030, A3 (B3) on the curve in $-3\sigma$ condition status in 2040, A4 (B4) on the curve in $-2\sigma$ condition status in 2050, and A5 (B5) on the curve in $-3\sigma$ condition status in 2060. Second, the future decarbonization path was assumed to fluctuate in a range of $\sigma$ at each stage. It is proposed that the future decarbonization path will be between the curve in the $-2\sigma$ and $-\sigma$ condition statuses during 2020–2030, and the change will be above and below the curve in the $-2\sigma$ condition status during 2030–2040 in a region of $\sigma$. In 2040–2050, the path changes between the curves in the $-3\sigma$ and $-2\sigma$ condition statuses, and in the final 2050–2060, it will fluctuate near the curve in the $-3\sigma$ condition status. Finally, the realization of the future decarbonization roadmap is dependent on the intervention situation of the emission reduction strategy of urban and rural residential buildings in China from now to 2060. It is expected that it will gradually enter a period of strong emission reduction and finally become stable. Hence, a future decarbonization path can be identified by fitting five control points within the limits of the path in the variable area.

Based on the dynamic simulation results presented in Section 4, annual emission parameter values (see Eqs. (3) and (4)) for the future emission paths under different condition statuses could be calculated, resulting in five emission control targets of urban and rural residential building operations. To achieve the carbon neutrality goal, carbon emissions benchmarks for urban residential buildings should be 380 MtCO$_2$ in 2030, 273 MtCO$_2$ in 2040, 85 MtCO$_2$ in 2050, and 28 MtCO$_2$ in 2060, whereas for rural regions, the benchmarks should be 269 MtCO$_2$ in 2030, 167 MtCO$_2$ in 2040, 44 MtCO$_2$ in 2050, and 14 MtCO$_2$ in 2060. In the socioeconomic and technological context of achieving the aforementioned five emission control targets, it is recommended to cap the energy intensity and energy-related carbon intensity of urban residential building operations at 8.9 kgce-m$^{-2}$ and 1.3 kgCO$_2$-kgce$^{-1}$ by 2030, and subsequently reduce them to 5.2 kgce-m$^{-2}$ and 0.1 kgCO$_2$-kgce$^{-1}$ by 2060. As for rural residential building operations, it is advisable to restrict the energy intensity and energy-related carbon intensity below 8.9 kgce-m$^{-2}$ and 1.3 kgCO$_2$-kgce$^{-1}$ by 2030, and by 2060, the energy intensity should be restrained from 10.9 kgce-m$^{-2}$ while the energy-related carbon intensity should reach 0.1 kgCO$_2$-kgce$^{-1}$; further details of the projected parameter values are presented in Table B2 (see Appendix B). In addition, these control targets are flexible within a range of variation (see Fig. 10 red variable areas); decarbonization targets can be adjusted accordingly to reflect actual conditions. Upon examining the likelihood of the four variable areas in the dynamic scenario, it was observed that the probability of the second area is 6.1%, which is nearly half of the first area (13.6%). Furthermore, the likelihood of the third and fourth areas is approximately 30% of the previous area’s probability. As decarbonization progresses, its goals become increasingly difficult to achieve. In general, it is immensely challenging to achieve carbon neutrality in China’s residential buildings by 2060, as evidenced by the extremely low probability shown in Fig. 10.

Furthermore, compared to other recent studies investigating decarbonization pathways for residential building operations in the context of China’s goal to achieve carbon neutrality by 2060, this study goes beyond by simulating the decarbonization potential of different end-use activities up to 2060. The simulations in this study reveal an earlier peak level and peaking time of energy and emissions in residential building operations compared to the results of Ma, Ma [71], indicating the urgency of achieving net-zero emissions by 2060. Therefore, this study highlights the need for accelerating decarbonization efforts in China’s residential buildings to meet the net-zero challenge by 2060. Looking towards a more positive outlook, if the first phase of the projected future decarbonization roadmap can be realized within the variable area, the possibility of subsequent future decarbonization roadmaps being achieved in accordance with the established plan will be greatly increased due to the superimposed benefits. Overall, Sections 5.1 and 5.2 positively answer Question 3 in Section 1.

5.3. Policy recommendations for decarbonizing residential building operations

Sections 5.1 and 5.2 present end-use benchmarks and phased emission control targets for the carbon peak and carbon neutrality goals,
Mandatory standards for energy efficiency of end-uses in residential buildings

- **Appliance**
  - **GB 12021.2 GB 19577**
  - **GB 21456 GB 38720**

- **Cooking**
  - **GB 21455 GB 12021.3 GB 19576**

- **Cooling**
  - **GB 25834 GB 26065**

- **Heating**
  - **GB 21519 GB 26969 GB 29541**

- **Hot Water**
  - **GB 38255 GB 19043 GB 19044 GB 19145**

- **Lighting**
  - **1989 1999 2009 2019**

Fig. 11. Past low carbon emission policies for residential building operation in China.

Overall, the policy recommendations presented in this section are the last step in addressing Question 3 raised in Section 1.

6. Conclusions

This study developed an end-use emission model to analyze the past decarbonization and projected emission change in China’s residential building operations by mid-century. Specifically, the study calculated the decarbonization achieved between 2001 and 2018 and illustrated the carbon emission paths from 2000 to 2060, identifying the energy and emissions peaks under various scenarios. Moreover, the energy benchmarks for end-uses in both urban and rural residential building operations in China were discussed, and the projected decarbonization path with phased decarbonization targets was planned. In addition, based on past emission reduction efforts and policies, a set of policy suggestions for building decarbonization were proposed.

6.1. Main findings

- The emission reduction from China’s residential building operations during 2001–2018 was 2.77 (± 1.61) GtCO$_2$, with varying reductions in four different periods: 296 (±446, 2001–2005), 636 (±446, 2006–2010), 929 (±446, 2011–2015), and 912 (±268, 2016–2018) MtCO$_2$. The emission reduction intensities for each period were 1.7 (±1.5), 3.2 (±1.5), 4.0 (±1.5), and 5.6 (±1.5) kgce·m$^{-2}$·year$^{-1}$ respectively. It is worth noting that decarbonization efforts in China’s residential building operations have steadily increased at different levels over the past two decades.

- **Residential building operations in China are expected to peak in 2031 (± 3), with a peak of 0.95 (± 0.06) GtCO$_2$.** The simulation results showed that under the BAU scenario, China’s urban residential buildings would reach a peak of 0.57 (±0.06) GtCO$_2$ in 2035 (±4), and the emissions peak of rural residential buildings would be 0.40 (±0.02) GtCO$_2$ in 2026 (±4). Moreover, this study found that energy-related carbon intensity and energy intensity are the key factors that influence the carbon peak and its peaking time in residential building operations. Furthermore, to achieve the carbon peak earlier, it is crucial to focus on controlling the end-use energy consumption of heating [262 (±1) Mtce] and appliances [65 (±2) Mtce] for urban residential buildings, while rural residential buildings...
should prioritize controlling the end-use consumption of heating (151 (±16) Mtce).

- To hit the carbon neutral goal by 2060, the carbon emissions of China’s residential building operations in 2030 should be controlled within 380 and 269 MtCO₂ for urban and rural regions, respectively. Through the assessment of emission parameters in key years under different emission scenarios, the future operational emission benchmarks of urban residential buildings would be 380 MtCO₂ in 2030, 273 MtCO₂ in 2040, 85 MtCO₂ in 2050, and 28 MtCO₂ in 2060, and those in rural buildings would be 269 MtCO₂ in 2030, 167 MtCO₂ in 2040, 44 MtCO₂ in 2050, and 14 MtCO₂ in 2060.

6.2. Future studies

Several gaps in this current work deserve to be further studied. First, according to sensitivity analysis, the key emission parameters affecting carbon peaks are energy-related carbon intensity and energy intensity; however, this study developed a bottom-up emission model by considering the energy intensity of end-use activity. In future studies, it would make sense to consider including sources of energy-related carbon intensity, such as coal and oil, in bottom-up emission model. Second, while this study considered scenarios with different probability conditions, including the 1.5 and 2 ºC target scenarios in further studies could explore the uncertainty of emission parameters. Moreover, the object of study could be expanded to explore the characteristics of carbon emissions in more countries or regions, such as various climate zones in China, other countries in Asia, or other continents. In addition, further research into decarbonization technologies and their effects could provide specific emission reduction recommendations for achieving the carbon neutral target of each country.

Author contributions

N Zhou, W Feng, and M Ma conceptualized the framework of this study. C Zou and M Ma contributed to the methodology, data collection, data calculation, and results analysis. S Zhang and K You helped to polish the original manuscript. All authors read, revised and approved the final version of the original manuscript.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

Data will be made available on request.

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Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.energy.2023.127689.

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