Title

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

Authors

Zou, Chenchen

Ma, Minda

Zhou, Nan

et al.

Publication Date

2023-08-01

DOI

10.1016/j.energy.2023.127689

Energy 277 (2023) 127689

Contents lists available at ScienceDirect

Energy

journal homepage: www.elsevier.com/locate/energy

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

Chenchen Zou [a,1], Minda Ma [b,1,2,*], Nan Zhou [b], Wei Feng [b], Kairui You [a], Shufan Zhang [a]

[a] School of Management Science and Real Estate, Chongqing University, Chongqing, 400045, PR China
[b] Building Technology and Urban Systems Division, Energy Technologies Area, Lawrence Berkeley National Laboratory, Berkeley, CA 94720, United States

ARTICLE INFO

Handling Editor: X Zhao

Keywords:
Residential building
Operational decarbonization
Emission path
End-use activity
Carbon neutrality
Dynamic emission scenario analysis

ABSTRACT

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 ($\pm$1.61) giga tons of carbon dioxide ($GtCO_2$). Dynamic simulation results of the emission model reveal that residential building operations will peak in 2031 ($\pm$3) with 0.95 ($\pm$0.06) $GtCO_2$. Energy-related carbon intensity ($\sim$44%) and energy intensity ($\sim$36%) are identified as the primary factors affecting carbon peak status, with heating ($\sim$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 $GtCO_2$ in 2030, respectively, and offsetting only 0.03 and 0.01 $GtCO_2$ 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 (CO_2) 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, this 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 CO_2 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?

* Corresponding author.
E-mail addresses: maminda@lbl.gov, maminda2020@tsinghua.org.cn (M. Ma).
[1] These authors contributed to the work equally and should be regarded as co-first authors.
[2] Homepage: https://scholar.google.com/citations?user=240qUyIAAAAJ&hl=en

https://doi.org/10.1016/j.energy.2023.127689
Received 14 February 2023; Received in revised form 15 April 2023; Accepted 28 April 2023
Available online 29 April 2023
0360-5442/

Abbreviations

BAU	Business as usual
EKC	Environmental Kuznets curve
GDP	Gross domestic product
Gtce	Giga tons of standard coal equivalent
$GtCO_2$	Giga tons of carbon dioxide
IPAT	Impact on population, affluence, and technology
kgce	Kilograms of standard coal equivalent
$kgCO_2$	Kilograms of carbon dioxide
Mtce	Mega tons of standard coal equivalent
$MtCO_2$	Mega tons of carbon dioxide
SD	Standard deviation

Symbols

C_r	Carbon emissions of residential buildings
$C_{r,r}$	Carbon emission of rural residential buildings
$C_{r,u}$	Carbon emission of urban residential buildings
ΔC_{ri}	Contribution of factor i to C_r
E	Energy consumption of residential buildings
ER_r	Emission reduction of residential building operation
e	Energy intensity of residential buildings
$e_{r,r}$	Energy intensity of rural residential buildings
$e_{r,u}$	Energy intensity of urban residential buildings
F	Floor space of residential buildings
$f_{r,r}$	Floor space per capita of rural residential buildings
$f_{r,u}$	Floor space per capita of urban residential buildings
K	Energy-related carbon intensity of residential buildings
$K_{r,r}$	Energy-related carbon intensity of rural residential buildings
$K_{r,u}$	Energy-related carbon intensity of urban residential buildings
m^2	Square meters
P	Population size
U	Urbanization level
ω	Random value
σ	Standard deviation

- How can future residential building operations decarbonize to achieve carbon neutrality?

To respond to these questions, this study undertakes a new direction by constructing a bottom-up model that considers end-use activity to analyze past emission reductions and simulate the projected emission change of China's urban and rural residential building operations by mid-century. Specifically, the study calculates decarbonization during 2001–2018 by using the Log-Mean Divisia Index (LMDI) method, and dynamic emission scenario analysis is used to illustrate carbon emission paths up to 2060, indicating the peaks of energy and emissions under different scenarios. Moreover, this study discusses energy benchmarks for six end uses in China's urban and rural residential building operations while outlining a projected decarbonization path with phased decarbonization targets. Finally, a set of policy suggestions for building decarbonization are proposed.

In the global effort to achieve carbon neutrality, this study's most important contribution is providing a dynamic carbon emission roadmap from a bottom-up perspective, particularly by identifying the step-by-step decarbonization potential in China's urban and rural residential building operations. Most current studies rely on static emission models to characterize future emissions and investigate the status of carbon peak or carbon neutrality, which lacks insight. Additionally, uncertainty arising from changes in emission model parameters is difficult to consider in static scenario model. To cover this gap, this study develops a dynamic emission scenario analysis based on a bottom-up model that considers end-use activities offering a stepwise data analysis benchmark for decarbonizing the urban and rural residential building operations of the top emitters. This contribution furthers global building decarbonization in the age of "Post Paris".

This study presents a literature review in Section 2; methods and data, including developing an emission model, emission reduction analysis and dynamic scenario simulation, are introduced in Section 3. Section 4 shows the past decarbonization and the dynamic emission roadmap to mid-century in China. Furthermore, the status and uncertainty of carbon peaks in urban and rural residential building operations are analyzed. Section 5.1 presents the energy benchmarks of six end uses in urban and rural residential building operations, Section 5.2 discusses the carbon neutral pathways of residential building operations, and Section 5.3 proposes corresponding policy measures. Finally, the main findings and future studies are summarized in Section 6.

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 [20] 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 CO_2 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 ($\pm$5) at 1.37 ($\pm$0.26) $GtCO_2$.

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 $GtCO_2$ and 2.42 $GtCO_2$ 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:

$$I = P \bullet A \bullet T \tag{1}$$

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 (C_r), as well as the carbon emission of China's urban residential buildings ($C_{r,u}$) and rural residential buildings ($C_{r,r}$). The model includes many factors that represent the emissions characteristics of residential building emissions, specifically the population (P), per capita floor space ($\frac{F}{P}$), energy intensity ($\frac{E}{F}$) and energy-related carbon intensity ($\frac{CO_2}{E}$), as shown in Eqs. (2)–(4), Fig. 1, and Table 1.

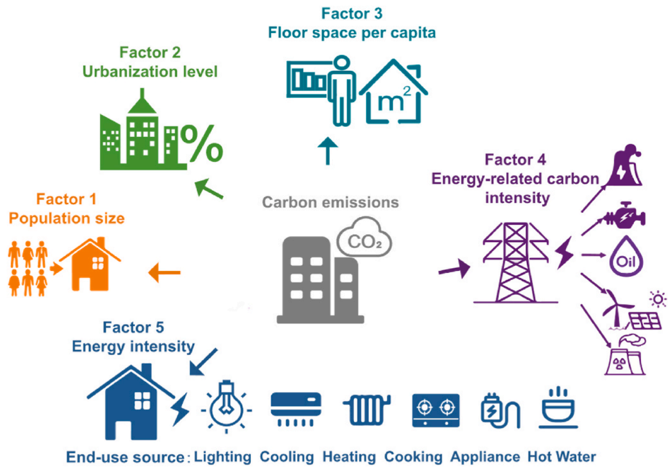

Fig. 1. Emission model of China's residential building operation based on the IPAT model.

Table 1
Emission model equation parameters (Eqs. (3) and (4)).

Symbol	Factor	Unit
$C_{r,u}$	Carbon emission of urban residential buildings	$GtCO_2$
$C_{r,r}$	Carbon emission of rural residential buildings	$GtCO_2$
P	Population size	Billion persons
U	Urbanization level	%
$f_{r,u}$	Floor space per capita of urban residential buildings	Square meters (m^2) · person^{-1}
$f_{r,r}$	Floor space per capita of rural residential buildings	m^2·person^{-1}
$K_{r,u}$	Energy-related carbon intensity of urban residential buildings	Kilograms of carbon dioxide per kilogram of standard coal equivalent ($kgCO_2$·kgce^{-1})
$K_{r,r}$	Energy-related carbon intensity of rural residential buildings	$kgCO_2$·kgce^{-1}
$e_{r,u}$	Energy intensity of urban residential buildings	kgce·m^{-2}
$e_{r,r}$	Energy intensity of rural residential buildings	kgce·m^{-2}

$$CO_2 = P \bullet \frac{F}{P} \bullet \frac{E}{F} \bullet \frac{CO_2}{E} \tag{2}$$

which can be summarized as follows:

$$C_{r,u} = P \bullet U \bullet f_{r,u} \bullet e_{r,u} \bullet K_{r,u} \tag{3}$$

$$C_{r,r} = P \bullet (1-U) \bullet f_{r,r} \bullet e_{r,r} \bullet K_{r,r} \tag{4}$$

$$C_r = C_{r,u} + C_{r,r} \tag{5}$$

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:

$$C_{r,u} = P \bullet U \bullet f_{r,u} \bullet \sum_x e_{u,x} \bullet K_{r,u} \tag{6}$$

$$C_{r,r} = P \bullet (1-U) \bullet f_{r,r} \bullet \sum_y e_{r,y} \bullet K_{r,r} \tag{7}$$

$$e_{r,u} = \sum_x e_{u,x}, e_{r,r} = \sum_y e_{r,y} \tag{8}$$

where $e_{u,x} \in (e_{u,h}, e_{u,a}, e_{u,ck}, e_{u,hw}, e_{u,cl}, e_{u,l}), e_{r,y} \in (e_{r,h}, e_{r,a}, e_{r,ck}, e_{r,hw}, e_{r,cl}, e_{r,l})$; e represents energy intensity, u denotes urban, r denotes rural, h denotes heating, a denotes appliance, ck denotes cooking, hw denotes hot water, cl denotes cooling, and l denotes lighting. For example, $e_{u,h}$ is defined as the energy intensity of heating end use in urban residential buildings.

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 ΔT ($\Delta C|_{0\to T}$) can be expressed as follows:

$$\Delta C|_{0\to T} = C_r|_T - C_r|_0 = \left(\Delta C_{rP} + \Delta C_{rU} + \Delta C_{rf} + \Delta C_{re} + \Delta C_{rK}\right)\Big|_{0\to T} \tag{9}$$

$$\Delta C_{rP} = \frac{C_r|_T - C_r|_0}{\ln C_r|_T - \ln C_r|_0} \bullet \ln\left(\frac{P|_T}{P|_0}\right) \tag{10}$$

Therefore, the equation to express the carbon emission reductions of residential building operations in China (ER_r) is:

$$ER_r|_{0\to T} = -\sum \Delta C_{ri}|_{0\to T} \tag{11}$$

where $\Delta C_{ri}|_{0\to T} \in (\Delta C_{rP}, \Delta C_{rU}, \Delta C_{rf}, \Delta C_{re}, \Delta C_{rK}), \Delta C_{ri}|_{0\to T} < 0$ (12)

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 [69], which is widely used in risk management. To control the variation in future carbon emissions, the random value (ω) 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.

$$C_r^{Dynamic} = C_r^{Static} \bullet \left(1 + \omega \bullet \frac{T - 2018}{2060 - 2018}\right), \omega \sim N\left(0, \sigma^2\right) \tag{13}$$

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 CBEED (www.cbeed.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 CO_2 ($MtCO_2$) per year for total reduction, ±63 $kgCO_2$ for CO_2 reduction per capita, and ±1.5 kgce·m^{-2} for 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) $GtCO_2$ (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 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) $MtCO_2$. 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 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) kgce·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 $MtCO_2$. 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 $GtCO_2$ and 2025 at 0.40 $GtCO_2$, 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 CO_2 emissions and energy demand tend to peak much later in urban regions than in rural 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) $GtCO_2$ and 0.69 (±0.04) giga tons of standard coal equivalent (Gtce[3]), 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) $GtCO_2$ and 0.48 (±0.04) Gtce, respectively. Meanwhile, it can also be observed that the carbon peak in rural areas is 0.40 (±0.02) $GtCO_2$, and the corresponding energy demand peak is 0.23 (±0.01) Gtce. 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.

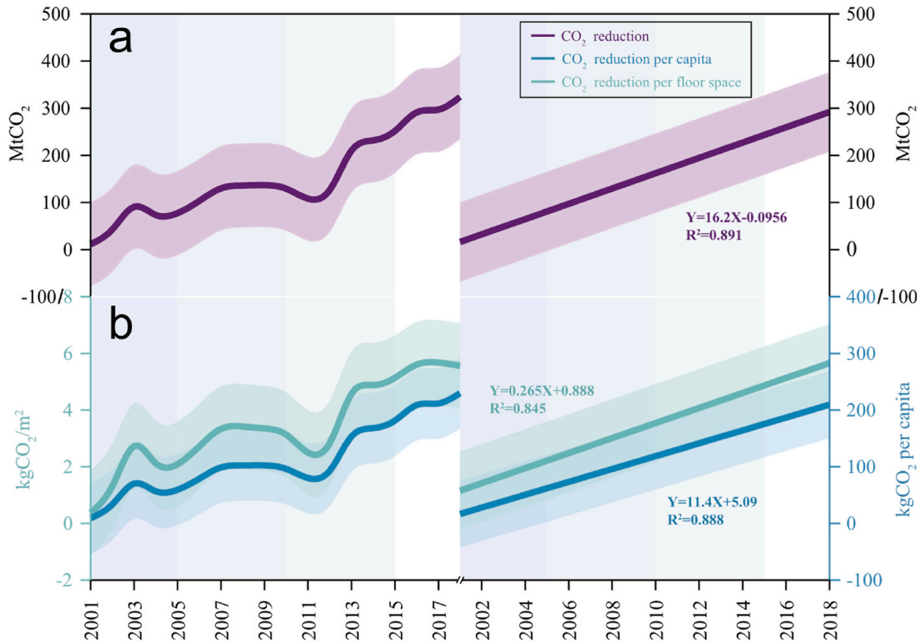

Fig. 2. Past decarbonization of residential building operations at the measures of (a) total reduction and (b) reduction per capita and per floor space.

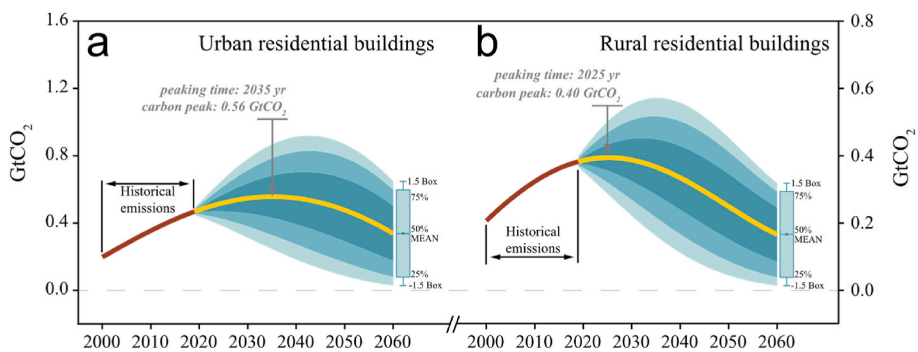

Fig. 3. Static paths of carbon emissions and dynamic carbon emission scenarios with varying probabilities in residential building operations up to 2060.

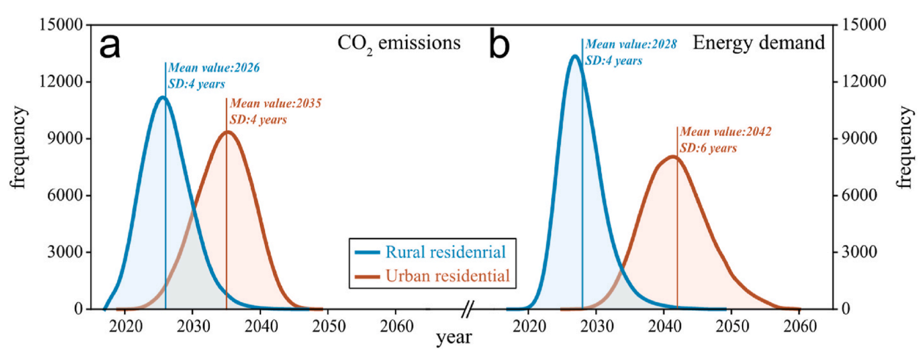

Fig. 4. Peaking time distributions of (a) CO_2 emissions and (b) energy demand in residential building operations.

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

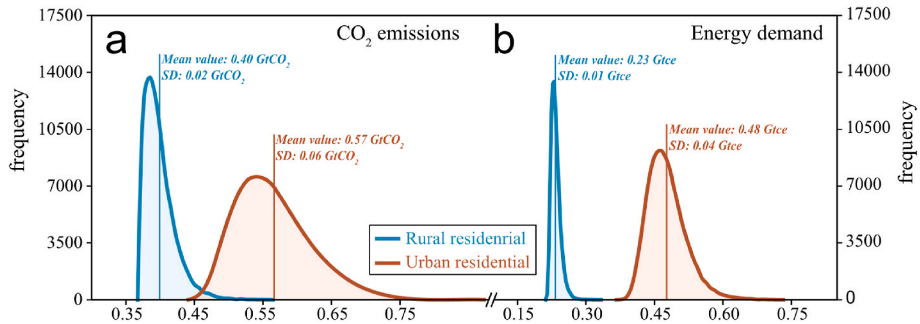

Fig. 5. Peak distributions of (a) CO_2 emissions and (b) energy demand in residential building operations.

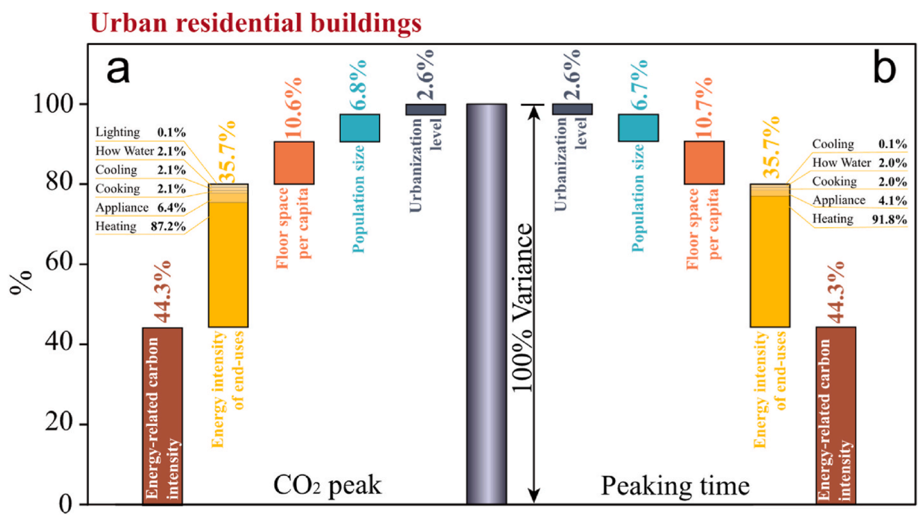

Fig. 6. Sensitivity analysis of the uncertainty of the (a) CO_2 peak and (b) peaking time in urban residential building operation.

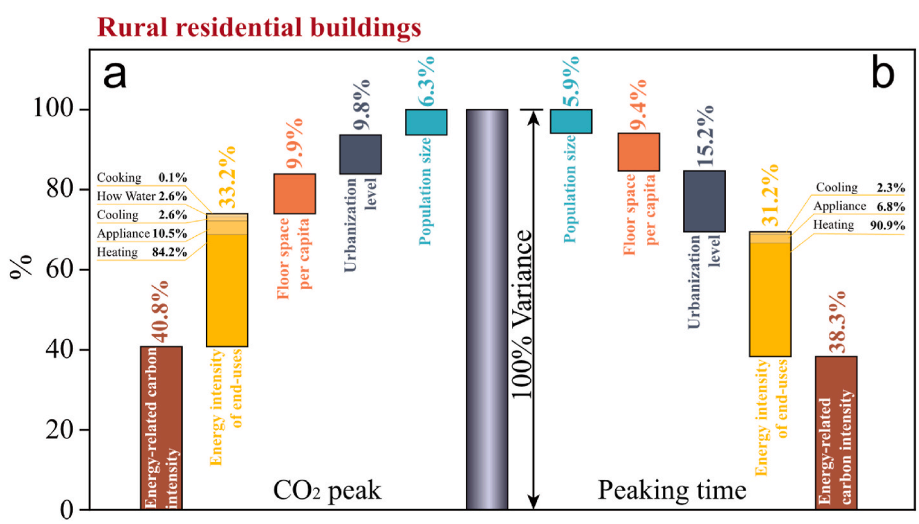

Fig. 7. Sensitivity analysis of the uncertainty of the (a) CO_2 peak and (b) peaking time in rural residential building operations.

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% (±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 the 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 ($\pm$0.06) $GtCO_2$ and 2026 at 0.40 ($\pm$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 ($\pm$2) mega tons of standard coal equivalent (Mtce), 78 ($\pm$4) Mtce, 49 Mtce, 262 ($\pm$1) Mtce, 53 Mtce, and 35 Mtce, respectively. The energy consumption of the six end-use activities in rural residential building operations should be restrained below the benchmark of 41 ($\pm$2) Mtce, 36 ($\pm$2) Mtce, 35 ($\pm$2) Mtce, 151 ($\pm$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 cooling, cooking, 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 $-\sigma$, -2σ, and -3σ 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 -2σ and $-\sigma$ scenarios, the probability of carbon emission paths is 13.6%, while between the -3σ and -2σ 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

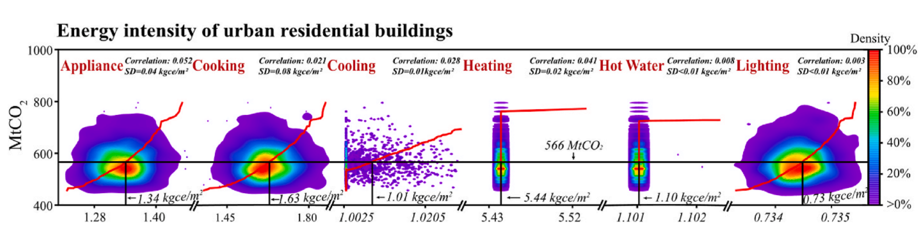

Fig. 8. Benchmarks of six end-use energy intensities in urban residential building operations.

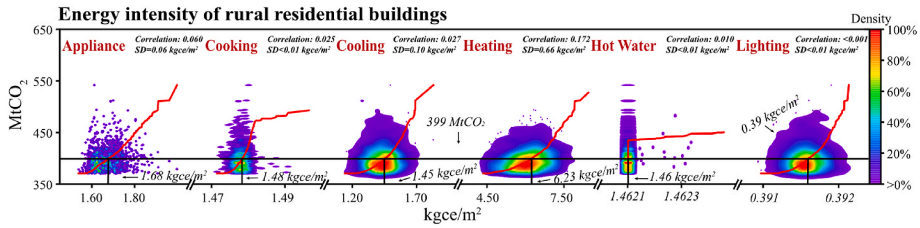

Fig. 9. Benchmarks of six end-use energy intensities in rural residential building operations.

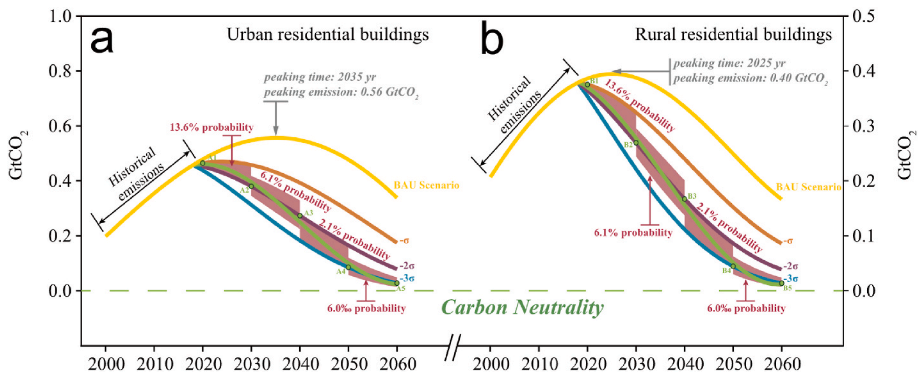

Fig. 10. Emission control plans for future residential building operations towards the carbon neutrality.

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 -2σ condition status in 2030, A3 (B3) on the curve in -2σ condition status in 2040, A4 (B4) on the curve in -3σ condition status in 2050, and A5 (B5) on the curve in -3σ condition status in 2060. Second, the future decarbonization path was assumed to fluctuate in a range of σ at each stage. It is proposed that the future decarbonization path will be between the curve in the -2σ and $-\sigma$ condition statuses during 2020–2030, and the change will be above and below the curve in the -2σ condition status during 2030–2040 in a region of σ. In 2040–2050, the path changes between the curves in the -3σ and -2σ condition statuses, and in the final 2050–2060, it will fluctuate near the curve in the -3σ 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 $kgce{\cdot}m^{-2}$ and 1.0 $kgCO_2{\cdot}kgce^{-1}$ by 2030, and subsequently reduce them to 5.2 $kgce{\cdot}m^{-2}$ and 0.1 $kgCO_2{\cdot}kgce^{-1}$ by 2060. As for rural residential building operations, it is advisable to restrict the energy intensity and energy-related carbon intensity below 8.9 $kgce{\cdot}m^{-2}$ and 1.3 $kgCO_2{\cdot}kgce^{-1}$ by 2030, and by 2060, the energy intensity should be restrained from 10.9 $kgce{\cdot}m^{-2}$ while the energy-related carbon intensity should reach 0.1 $kgCO_2{\cdot}kgce^{-1}$; 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, respectively. This section proposes policy recommendations to achieve these objectives and answers Question 3 from Section 1 by reviewing decarbonization policies for China's residential building operations.

Mandatory standards are considered the most direct and powerful policies for limiting energy consumption and improving energy efficiency levels in residential buildings [72,73]. Since the 1980s, China has issued building energy efficiency standards for various temperature zones to curb the energy consumption of residential buildings. For example, the design standard for the energy efficiency of residential buildings in severely cold and cold zones, as stipulated by JGJ-26 has undergone several updates, and the 2018 standard achieved an energy conservation level of 75%. Among the energy efficiency standards for end-use activities in residential buildings, cooling end-use activity has been restricted earlier, and these mandatory standards have improved energy efficiency by specifying minimum energy efficiency limits for end uses, which corresponded to higher requirements for end-use energy efficiency technology [74]. The evolution of residential building design and end-use energy efficiency standards are presented in Fig. 11.

To achieve the goals of carbon peak and carbon neutrality earlier, based on the end-use benchmarks and phased emission targets proposed in Sections 5.1 and 5.2, as well as past policy reviews, several policy recommendations are presented below:

- The use of an integrated framework of energy and emissions information dataset [75] should be adopted to aid policy formulation for the characteristics of urban and rural residential buildings in China.
- Targeted energy conservation and efficiency standards should be proposed for end-use activities [76] (especially in heating and appliance end-use activities) to achieve carbon neutral phase objectives.
- Financial investment [77] to retrofit existing residential buildings [78] should be increased to realize full coverage of standard energy efficiency rates for all residential buildings.
- The development of low-carbon technologies and the utilization of clean energy [79] and mixed energy decarbonization in residential buildings should be promoted to accelerate decarbonization [80].
- Under the overall decarbonization plan, periodic decarbonization measures should be adjusted through continuous adaptation of the actual emission reduction effect [81].

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) $kgce{\cdot}m^{-2}{\cdot}year^{-1}$, 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

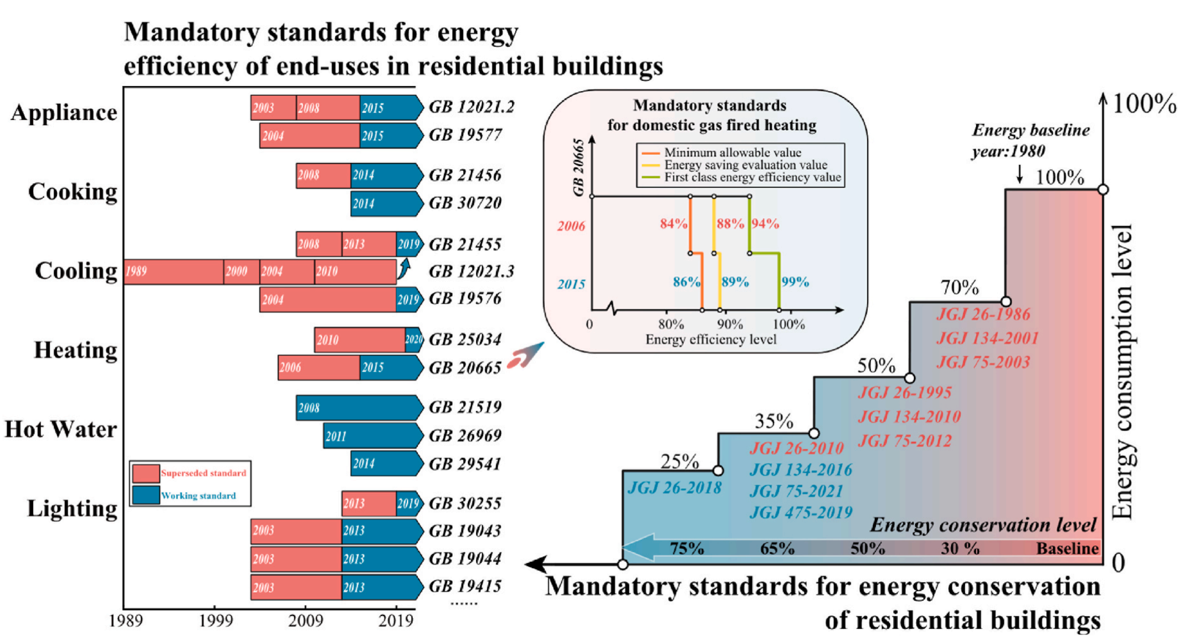

Fig. 11. Past low carbon emission policies for residential building operation in China.

should prioritize controlling the end-use consumption of heating [151 (±16) Mtce].

- **To hit the carbon neural goal by 2060, the carbon emissions of China's residential building operations in 2030 should be controlled within 380 and 269 $MtCO_2$ 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 $MtCO_2$ in 2030, 273 $MtCO_2$ in 2040, 85 $MtCO_2$ in 2050, and 28 $MtCO_2$ in 2060, and those in rural buildings would be 269 $MtCO_2$ in 2030, 167 $MtCO_2$ in 2040, 44 $MtCO_2$ in 2050, and 14 $MtCO_2$ 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 °C 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.

Acknowledgment

This manuscript has been authored by an author at Lawrence Berkeley National Laboratory under Contract No. DE-AC02-05CH11231 with the U.S. Department of Energy. The U.S. Government retains, and the publisher, by accepting the article for publication, acknowledges, that the U.S. Government retains a non-exclusive, paid-up, irrevocable, world-wide license to publish or reproduce the published form of this manuscript, or allow others to do so, for U.S. Government purposes.

Appendix A. Supplementary data

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

References

[1] UNEP. GlobalABC Global status report for buildings and construction. 2021. Available at: https://www.unep.org/resources/report/2021-global-status-report-buildings-and-construction; 2021.
[2] IEA. World. Energy outlook 2021. Paris: IEA; 2021. Available at: https://www.iea.org/reports/world-energy-outlook-2021.
[3] Chen L, Ma M, Xiang X. Decarbonizing or illusion? How carbon emissions of commercial building operations change worldwide. Sustain Cities Soc 2023. Forthcoming.
[4] IEA. Tracking buildings 2021. Paris: IEA; 2021. Available at: https://www.iea.org/reports/tracking-buildings-2021.
[5] Qiu S, Lei T, Wu JT, Bi SS. Energy demand and supply planning of China through 2060. Energy 2021;234:121193.
[6] Zhao J, Jiang Q, Dong X, Dong K, Jiang H. How does industrial structure adjustment reduce CO2 emissions? Spatial and mediation effects analysis for China. Energy Econ 2022;105:105704.
[7] You K, Ren H, Cai W, Huang R, Li Y. Modeling carbon emission trend in China's building sector to year 2060. Resour Conserv Recycl 2023;188:106679.
[8] Yan R, Chen M, Xiang X, Feng W, Ma M. Heterogeneity or illusion? Track the carbon Kuznets curve of global residential building operations. Appl Energy 2023. Forthcoming.
[9] Cheng YS, Li R, Woo CK. Regional energy-growth nexus and energy conservation policy in China. Energy 2021;217:119414.
[10] Malla S. An outlook of end-use energy demand based on a clean energy and technology transformation of the household sector in Nepal. Energy 2022;238:121810.
[11] Taniguchi-Matsuoka A, Shimoda Y, Sugiyama M, Kurokawa Y, Matoba H, Yamasaki T, et al. Evaluating Japan's national greenhouse gas reduction policy using a bottom-up residential end-use energy simulation model. Appl Energy 2020;279:115792.
[12] Fan JL, Yu H, Wei YM. Residential energy-related carbon emissions in urban and rural China during 1996-2012: from the perspective of five end-use activities. Energy Build 2015;96:201–9.
[13] Stanford Earth Matters magazine. The science behind decarbonization. Available at: https://earth.stanford.edu/news/science-behind-decarbonization; 2021.
[14] Torchio MF, Lucia U, Grisolia G. Economic and human features for energy and environmental indicators: a tool to assess countries' progress towards sustainability. Sustainability (Switzerland) 2020;12(22):1–19.
[15] Grisolia G, Lucia U, Torchio MF. Sustainable development and workers ability: considerations on the education index in the human development index. Sustainability (Switzerland) 2022;14(14):8372.
[16] Grisolia G, Fino D, Lucia U. The education index in the context of sustainability: thermo-economic considerations. Front Phys 2022;10:968033.
[17] Lucia U, Fino D, Grisolia G. A thermoeconomic indicator for the sustainable development with social considerations: a thermoeconomy for sustainable society. Environ Dev Sustain 2022;24(2):2022–36.
[18] Lucia U, Grisolia G. Biofuels analysis based on the THDI indicator of sustainability. Front Energy Res 2021;9:794682.
[19] Langevin J, Harris CB, Reyna JL. Assessing the potential to reduce U.S. Building CO2 emissions 80% by 2050. Joule 2019;3(10):2403–24.
[20] Langevin J, Harris CB, Satre-Meloy A, Chandra-Putra H, Speake A, Present E, et al. US building energy efficiency and flexibility as an electric grid resource. Joule 2021;5(8):2102–28.
[21] Lin YC, Ma LW, Li Z, Ni WD. The carbon reduction potential by improving technical efficiency from energy sources to final services in China: an extended Kaya identity analysis. Energy 2023;263:125963.
[22] Sadorsky P. Wind energy for sustainable development: driving factors and future outlook. J Clean Prod 2021;289:125779.
[23] González-Torres M, Pérez-Lombard L, Coronel JF, Maestre IR. A cross-country review on energy efficiency drivers. Appl Energy 2021;289:116681.
[24] Zhou X, Yu Y, Yang F, Shi Q. Spatial-temporal heterogeneity of green innovation in China. J Clean Prod 2021;282:124464.
[25] Song F, Su F, Mi C, Sun D. Analysis of driving forces on wetland ecosystem services value change: a case in Northeast China. Sci Total Environ 2021;751:141778.
[26] He J, Yue Q, Li Y, Zhao F, Wang H. Driving force analysis of carbon emissions in China's building industry: 2000–2015. Sustain Cities Soc 2020;60:102268.
[27] Zhong X, Hu M, Deetman S, Rodrigues JFD, Lin H-X, Tukker A, et al. The evolution and future perspectives of energy intensity in the global building sector 1971–2060. J Clean Prod 2021;305:127098.
[28] Karmellos M, Kosmadakis V, Dimas P, Tsakanikas A, Fylaktos N, Taliotis C, et al. A decomposition and decoupling analysis of carbon dioxide emissions from electricity generation: evidence from the EU-27 and the UK. Energy 2021;231:120861.
[29] Zhao J, Jiang Q, Dong X, Dong K. Would environmental regulation improve the greenhouse gas benefits of natural gas use? A Chinese case study. Energy Econ 2020;87:104712.
[30] Fang K, Li C, Tang Y, He J, Song J. China's pathways to peak carbon emissions: new insights from various industrial sectors. Appl Energy 2022;306:118039.
[31] Dong K, Sun R, Li H, Liao H. Does natural gas consumption mitigate CO2 emissions: testing the environmental Kuznets curve hypothesis for 14 Asia-Pacific countries. Renew Sustain Energy Rev 2018;94:419–29.
[32] Tang B-J, Guo Y-Y, Yu B, Harvey LDD. Pathways for decarbonizing China's building sector under global warming thresholds. Appl Energy 2021;298:117213.

[33] Hou H, Feng X, Zhang Y, Bai H, Ji Y, Xu H. Energy-related carbon emissions mitigation potential for the construction sector in China. Environ Impact Assess Rev 2021;89:106599.
[34] Zhang S, Ma M, Xiang X, Cai W, Feng W, Ma Z. Potential to decarbonize the commercial building operation of the top two emitters by 2060. Resour Conserv Recycl 2022;185:106481.
[35] Sun Y, Li M, Zhang M, Khan HSUD, Li J, Li Z, et al. A study on China's economic growth, green energy technology, and carbon emissions based on the Kuznets curve (EKC). Environ Sci Pollut Control Ser 2021;28(6):7200–11.
[36] Li JJ, Tian YJ, Deng YL, Zhang YL, Xie KC. Improving the estimation of greenhouse gas emissions from the Chinese coal-to-electricity chain by a bottom-up approach. Resour Conserv Recycl 2021;167:105237.
[37] Zhao G, Yu B, An R, Wu Y, Zhao Z. Energy system transformations and carbon emission mitigation for China to achieve global 2 degrees C climate target. J Environ Manag 2021;292:112721.
[38] Yang T, Pan Y, Yang Y, Lin M, Qin B, Xu P, et al. CO 2 emissions in China's building sector through 2050: a scenario analysis based on a bottom-up model. Energy 2017;128:208–23.
[39] Wen L, Li Z. Driving forces of national and regional CO2 emissions in China combined IPAT-E and PLS-SEM model. Sci Total Environ 2019;690:237–47.
[40] Ehrlich PR, Holdren JP. Impact of population growth. Science 1971;171(3977): 1212–7.
[41] Shuai C, Shen L, Jiao L, Wu Y, Tan Y. Identifying key impact factors on carbon emission: evidences from panel and time-series data of 125 countries from 1990 to 2011. Appl Energy 2017;187:310–25.
[42] Zhang P, Wang H. Do provincial energy policies and energy intensity targets help reduce CO2 emissions? Evidence from China. Energy 2022;245:123275.
[43] Li K, Ma M, Xiang X, Feng W, Ma Z, Cai W, et al. Carbon reduction in commercial building operations: a provincial retrospection in China. Appl Energy 2022;306: 118098.
[44] Zhang S, Ma M, Li K, Ma Z, Feng W, Cai W. Historical carbon abatement in the commercial building operation: China versus the US. Energy Econ 2022;105: 105712.
[45] Ma M, Feng W, Huo J, Xiang X. Operational carbon transition in the megalopolises' commercial buildings. Build Environ 2022;226:109705.
[46] Dong K, Dong X, Dong C. Determinants of the global and regional CO2 emissions: what causes what and where? Appl Econ 2019;51(46):5031–44.
[47] Liu Y, Feng C. Decouple transport CO2 emissions from China's economic expansion: a temporal-spatial analysis. Transport Res Transport Environ 2020;79: 102225.
[48] Yan R, Xiang X, Cai W, Ma M. Decarbonizing residential buildings in the developing world: historical cases from China. Sci Total Environ 2022;847:157679.
[49] Yan Y, Zhang H, Long Y, Zhou X, Liao Q, Xu N, et al. A factor-based bottom-up approach for the long-term electricity consumption estimation in the Japanese residential sector. J Environ Manag 2020;270:110750.
[50] Lin B, Ma R. Green technology innovations, urban innovation environment and CO2 emission reduction in China: fresh evidence from a partially linear functional-coefficient panel model. Technol Forecast Soc Change 2022;176:121434.
[51] Wang C, Wang F, Zhang X, Yang Y, Su Y, Ye Y, et al. Examining the driving factors of energy related carbon emissions using the extended STIRPAT model based on IPAT identity in Xinjiang. Renew Sustain Energy Rev 2017;67:51–61.
[52] Shimoda Y, Asahi T, Taniguchi A, Mizuno M. Evaluation of city-scale impact of residential energy conservation measures using the detailed end-use simulation model. Energy 2007;32(9):1617–33.
[53] Atikol U, Dagbasi M, Guven H. Identification of residential end-use loads for demand-side planning in northern Cyprus. Energy 1999;24(3):231–8.
[54] Gi K, Sano F, Hayashi A, Tomoda T, Akimoto K. A global analysis of residential heating and cooling service demand and cost-effective energy consumption under different climate change scenarios up to 2050. Mitig Adapt Strategies Glob Change 2018;23(1):51–79.
[55] Xiang X, Ma M, Ma X, Chen L, Cai W, Feng W, et al. Historical decarbonization of global commercial building operations in the 21st century. Appl Energy 2022;322: 119401.
[56] González-Torres M, Pérez-Lombard L, Coronel JF, Maestre IR, Paolo B. Activity and efficiency trends for the residential sector across countries. Energy Build 2022;273: 112428.
[57] Wang M, Feng C. Decoupling economic growth from carbon dioxide emissions in China's metal industrial sectors: a technological and efficiency perspective. Sci Total Environ 2019;691:1173–81.
[58] Khanna N, Fridley D, Zhou N, Karali N, Zhang J, Feng W. Energy and CO2 implications of decarbonization strategies for China beyond efficiency: modeling 2050 maximum renewable resources and accelerated electrification impacts. Appl Energy 2019;242:12–26.
[59] Rodriguez M. Why do many prospective analyses of CO2 emissions fail? An illustrative example from China. Energy 2022;244:123064.
[60] Ang BW. LMDI decomposition approach: a guide for implementation. Energy Pol 2015;86:233–8.
[61] Ma M-D, Chen M-X, Feng W, Huo J-W. What decarbonized the residential building operation worldwide since the 2000s. Petrol Sci 2022;19(6):3194–208.
[62] Lin B, Long H. Emissions reduction in China's chemical industry - based on LMDI. Renew Sustain Energy Rev 2016;53:1348–55.
[63] Zhang S, Zhou N, Feng W, Ma M, Xiang X, You K. Pathway for decarbonizing residential building operations in the US and China beyond the mid-century. Appl Energy 2023;342:121164.
[64] Zhang F, Deng X, Xie L, Xu N. China's energy-related carbon emissions projections for the shared socioeconomic pathways. Resour Conserv Recycl 2021;168:105456.
[65] Feng C, Huang JB, Wang M. The driving forces and potential mitigation of energy-related CO2 emissions in China's metal industry. Resour Pol 2018;59:487–94.
[66] Li J, Song X, Guo Y, Yang Q, Feng K. The determinants of China's national and regional energy-related mercury emission changes. J Environ Manag 2019;246: 505–13.
[67] Na W, Wang MM. A Bayesian approach with urban-scale energy model to calibrate building energy consumption for space heating: a case study of application in Beijing. Energy 2022;247:123341.
[68] Robati M, Oldfield P. The embodied carbon of mass timber and concrete buildings in Australia: an uncertainty analysis. Build Environ 2022;214:108944.
[69] Wang H, Lu X, Deng Y, Sun Y, Nielsen CP, Liu Y, et al. China's CO2 peak before 2030 implied from characteristics and growth of cities. Nat Sustain 2019;2(8): 748–54.
[70] Zhou N, Price L, Yande D, Creyts J, Khanna N, Fridley D, et al. A roadmap for China to peak carbon dioxide emissions and achieve a 20% share of non-fossil fuels in primary energy by 2030. Appl Energy 2019;239:793–819.
[71] Ma M, Ma X, Cai W, Cai W. Low carbon roadmap of residential building sector in China: historical mitigation and prospective peak. Appl Energy 2020;273:115247.
[72] Letschert V, Desroches LB, Ke J, McNeil M. Energy efficiency - how far can we raise the bar? Revealing the potential of best available technologies. Energy 2013;59: 72–82.
[73] Zhou S, Xu ZW. Energy efficiency assessment of RCEP member states: a three-stage slack based measurement DEA with undesirable outputs. Energy 2022;253:124170.
[74] Lo Piano S, Smith ST. Energy demand and its temporal flexibility: approaches, criticalities and ways forward. Renew Sustain Energy Rev 2022;160:112249.
[75] Qin C, Zhao J, Chen L, Liu Y, Wang W. An adaptive piecewise linearized weighted directed graph for the modeling and operational optimization of integrated energy systems. Energy 2022;244:122616.
[76] González-Torres M, Pérez-Lombard L, Coronel JF, Maestre IR, Yan D. A review on buildings energy information: trends, end-uses, fuels and drivers. Energy Rep 2022; 8:626–37.
[77] Khan Z, Ali S, Dong K, Li RYM. How does fiscal decentralization affect CO2 emissions? The roles of institutions and human capital. Energy Econ 2021;94: 105060.
[78] Jie PF, Zhang FH, Fang Z, Wang HB, Zhao YF. Optimizing the insulation thickness of walls and roofs of existing buildings based on primary energy consumption, global cost and pollutant emissions. Energy 2018;159:1132–47.
[79] Wang Y, Chi P, Nie R, Ma X, Wu WQ, Guo BH. Self-adaptive discrete grey model based on a novel fractional order reverse accumulation sequence and its application in forecasting clean energy power generation in China. Energy 2022; 253:124093.
[80] Daioglou V, Mikropoulos E, Gernaat D, van Vuuren DP. Efficiency improvement and technology choice for energy and emission reductions of the residential sector. Energy 2022;243:122994.
[81] Zhang X, Geng Y, Shao S, Wilson J, Song X, You W. China's non-fossil energy development and its 2030 CO2 reduction targets: the role of urbanization. Appl Energy 2020;261:114353.