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Building stock energy modeling to assess annual progress in stock energy efficiency and carbon emission reduction of commercial buildings

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ABSTRACT

Short-term progress assessments of carbon dioxide emission reductions are essential for nations to meet their medium/long-term targets. Bottom-up building stock energy modeling (BSEM) methods can contribute to this issue but have not been applied because of the need to represent short-term building stock dynamics in building systems and energy conservation measures (ECMs). To fill this gap, this study developed a BSEM framework that integrates top-down building stock decomposition, including building systems and ECMs, and bottom-up physics-based energy demand quantification using reference building models representing building stock segments. The framework was verified through a case study of a Japanese commercial building stock. The results indicate that the developed model effectively captures the short-term dynamics and contributions of the technologies. Although there are significant errors in estimating some building subsectors and end uses, the model predicts the changes in the aggregated energy consumption with acceptable accuracy. The Japanese 2030 emission reduction target cannot be achieved with the current technology deployment trends; however, the shortfall can be addressed by applying additional measures. Owing to its applicability to diverse building stocks, the framework promotes the use of BSEM for policy assessment and evidence-based policymaking for climate change mitigation.

1. Introduction

Several countries have reached a consensus on climate change mitigation, represented by the 1.5°C climate goal and long-term carbon neutrality commitment [1]. Many of these countries have set medium-term emission reduction targets for 2030 and are committed to updating their mitigation plans every 5 years [2]. Additionally, the emission reductions achieved by them are reported annually or biennially [3,4]. Short-term progress assessment is essential to identify necessary changes to stay on track to achieve medium/long-term reduction targets.

Econometric and other top-down methods [5] that incorporate macro-socioeconomic data have been employed to track and report the progress in national emission reduction (e.g., Switzerland [6], China [7], and Japan [8]). These methods are effective in quantifying the general reduction progress [9] but fail to specify the technologies that deliver these reductions [10]. In addition, these methods are sensitive to socioeconomic changes such as those caused by the COVID-19 pandemic. These limitations are particularly problematic in the building sector, where emission reductions depend on the technology deployment and significant social changes have been reported [11].

Some countries have adopted bottom-up quantification methods to assess the progress in reduction. For example, Japan has specified mitigation measures that contribute to its 2030 target and has reported the annual progress in emission reduction [12]. The Climate Change Committee in the UK is an example of an organization that has established specific indicators to monitor changes in the building sector and quantify the reduction effects [13]. Nevertheless, these frameworks do not fully capture the complexity of technology deployment and the corresponding reduction that has been achieved because simple modeling methods are used based on empirical data, expert judgment, or scenarios, and it is difficult to explore alternative pathways.

In such tasks, the use of bottom-up building stock energy modeling (BSEM) methods may offer valuable insights. However, these methods have not been applied yet.

1.1. Related works

Bottom-up BSEM methods generally calculate the energy consumption of a building stock by aggregating the product of the energy use

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Nomenclature

General terms

BAT	Best available technologies
BSEM	Building stock energy modeling
CO_2	Carbon dioxide
ECM	Energy conservation measure
EUI	Energy use intensity
HVAC	Heating, ventilating, and air-conditioning
IDA	Index decomposition analysis
LED	Light-emitting diode
NDC	Nationally Determined Contribution
PGWC	Plan for global warming countermeasures
RBM	Reference building model
TFA	Total floor area
WH	Water heating

Building system related terms

AHU	Air handling unit
CAV	Constant air volume
CO_2V	Air intake control based on CO_2 concentration in a conditioned space
FCU	Fan coil unit
HEX	Total heat exchanger in the ventilation
HP	Heat pump
NaV	Natural ventilation
OHU	Outdoor air handling unit
VAV	Variable air volume control
VRF	Variable refrigerant flow
VWV	Variable water volume control

intensity (EUI) per unit, typically appliances and building floor area, and the number of units N as $\sum_{m=1}^{M} EUI_m \times N_m$, where m represents the modeled segments, i.e., end use types and building stock segments [14]. The reduction can be quantified as $\sum_{m=1}^{M} \Delta EUI_m \times \Delta N_m$, where Δ indicates the changes. EUI_m and ΔEUI_m are modeled by scenarios, statistical or machine learning methods, and physics-based or reduced-order simulations [15,16]. For N_m and ΔN_m, many studies have constructed stock models based on the material flow analysis approach [17] (e.g., [18]).

Table 1 summarizes the studies that have used the bottom-up BSEM for policy assessment, including that of commercial building stocks. The table indicates the considered building types and modeling methods for

Table 1
Overview of the existing building stock energy models applied for policy assessment.

Literature	Type	Demand-side mitigation measures	EUI quantification	ΔN	ΔEUI	Validation	Assessment Period
Camarasa et al. [19]	B	I, W, HVAC, A, L, ECMs	Physics-based + Statistical	MFA + CO	CO+ SE+ SB	None	Long-term (2020–2050)
Eom et al. [20]	B	H, W, A, L	Statistical	CO	SE	None	Long-term (2005–2095)
Shi et al. [21]	B	I, W, HVAC, E, A, L	Statistical	MFA	CO	None	Long-term (2020–2050)
Wang et al. [22]	B	I, W, HVAC, E, A, L	Statistical	MFA	CO	None	Long-term (2010–2050)
Chen et al. [23]	B	H, W, A, L	Statistical	CO	SE	None	Long-term (2015–2100)
Zhang and Luo [24]	C	H	Statistical	CO	SE	None	Long-term (2020–2060)
Broin et al. [25]	B	End-use (H, W, A)	Statistical	SE	SE	None	Long-term (2005–2050)
Yang et al. [26]	B	End-use (H, E, A, L)	Statistical	SE	SE	None	Long-term (2005–2050)
Zhou et al. [27]	B (C)	End-use (H, E, L)	Statistical	SE	SE	None	Long-term (2010–2050)
Heeren et al. [29]	R	I, H, V, A	Physics-based	MFA	SE+ CO	None	Long-term (2005–2050)
Sandberg et al. [30]	B	I, W, HVAC, L	Statistical	MFA	SE	None	Medium-term (2020–2024, 2025–2034, 2035–2050)
Foliente and Seo [31]	C	I, W, HVAC, A, L	Physical-based	SE	SE	A-E	Medium-term (2006–2020)
Langevin et al. [36]	B	I, W, HVAC, A, L, ECMs	Physics-based + Statistical	CO	SB	None	Long-term (2015–2050)
Tang et al. [37]	B (C)	H	Statistical	SE	CO	None	Long-term (2016–2050)
Hirvonen et al. [38]	B	I, V, H, L	Statistical	MFA	CO	A-E	Long-term (2020–2050)
Hu et al. [39]	B	I, W, HAVC	Physics-based + Statistical	MFA	SE+ SB	A-E, A-EUI	Short-term, 2010–2020
Nageli et al. [40,41]	R	I, HVAC	Statistical	CO	SE+ CO	A-E, A-S,	Long-term (2020–2050)
Yamaguchi et al. [14]	C	I, W, HVAC, A, L, ECMs	Physics-based + Statistical	SE	SE+ SB	A-EUI	Medium-term (2013–2030)
Present study	C	I, W, HVAC, A, L, ECMs	Physics-based + Statistical	MFA	SE+ SB	A-E, D-E, D-S, D-EE	Short-term (2013–2021), medium-term (2021–2030)

Notations: Type: B: building sector, R: residential sector, C: commercial sector; **Mitigation measures**: I: Insulation, H: Space heating, W: Water heating, E: Equipment, A: Appliance, L: Lighting, V: Ventilation, HVAC: Heating, Ventilation and Air-conditioning system, ECMs: other energy conservation measures; **ΔN and ΔEUI**: MFA: Material flow analysis, SE: Scenarios and expert evaluation, SB: Surveys or measurements from sample buildings, CO: Cost optimization; **Validation**: A: Comparison with statistics in aggregated level; D: Comparison with statistics in disaggregated level, E: Energy consumption, EUI: Energy use intensity, S: Stock composition, EE: Energy efficiency.

EUI and *N*. The most frequent application is the estimation of the reduction potential and assessment of the feasibility of achieving long-term reduction targets. Camarasa et al. [19] integrated models developed for 32 countries to create a carbon emission reference and decarbonization scenarios for 2050. This study demonstrates the usefulness of the bottom-up BSEM to quantify the effects of technology deployment.

Eom et al. [20] presented a model for quantifying EUI_m using scenarios to identify long-term decarbonization opportunities. Shi et al. [21], Wang et al. [22], Chen et al. [23], and Zhang and Luo [24] conducted similar scenario-based quantifications. Broin et al. [25] established a method to represent the stock changes, energy efficiency, and energy structures in the European Union building stock. Yang et al. [26] developed a model that considered end use as the modeling unit and examined scenarios involving alteration of the building floor space and CO_2 emission intensity in the Chinese building sector. Zhou et al. [27] enhanced the resolution of scenarios by considering the technology packages in the Chinese building sector.

Mata et al. [28] developed a physics-based model using reference building models (RBMs), also called building archetypes, to quantify the EUI using physics-based simulation. Heeren et al. [29] developed an RBM-based model to consider the stock composition in terms of the insulation performance. Sandberg et al. [30] examined the use of heat pumps and renewable energy generation technologies in Norway. Foliente and Seo [31] examined energy efficiency improvement in various end uses. The use of RBMs enables the examination of the effects of physical and technical changes in the building stock. Carnieletto et al. [32] developed models that considered variations in the building's geometric characteristics. Kim et al. [33] and Yamaguchi et al. [14] enhanced building systems and energy conservation measures (ECMs), whereas Azar and Menassa [34] and Kim et al. [35] enhanced the operation-related characteristics. Langevin et al. [36] developed a method to explore the CO_2 emission reduction pathways in U.S. building stock by 2050, in which cost optimization was performed for RBMs to select the adopted ECMs. Tang et al. [37] developed a model to identify cost-optimal clean spaces and water heating pathways in northern China. Hirvonen et al. [38] proposed optimal retrofit solutions that minimized the lifecycle costs and energy consumption of Finnish building stocks. These optimization methods are useful for long-term policy assessment, including financial measures, but are not easy to apply to the assessment of short-term reduction progress because it is difficult to calibrate the model to accurately represent the baseline development.

Only a few studies have considered the short-term dynamics of the building stock. Hu et al. [39] evaluated the energy in building operations and the embodied energy in building construction in addition to emissions in China. Their model tracked the annual stock changes through building construction and demolition, considering the population growth, urbanization rates, and per capita floor area. However, the mitigation technologies were not analyzed in detail. Nägeli et al. [40] proposed a synthetic building stock modeling approach for residential buildings in Switzerland using an agent-based model with statistical methods that accounted for stock dynamics and retrofit options. The agent-based model was used to evaluate energy and emissions from 2000 to 2017 considering policy interventions [41]. However, no similar study has been conducted on commercial building stocks.

Table 1 lists the mitigation measures and validation methods employed in the listed studies. Several studies have considered insulation of the building envelope and changes in the heat source of water and space heating systems. Appliances, lighting, and ECMs are generally minimally addressed. These mitigation measures should be comprehensively addressed. Furthermore, the developed models have not been comprehensively validated. Hu et al. [39] and Yamaguchi et al. [14] validated their models using EUI at the building level. Foliente an Seo [31], Hirvonen et al. [38], Hu et al. [39] and Nägeli et al. [40] evaluated their results by comparing them with the national total energy consumption in specific years.

1.2. Research gap and aim

Useful BSEM methods have been established and applied to estimate the CO_2 emission reduction potential for long-term policy design. However, the BSEM has not been applied to the assessment of the short-term reduction progress for commercial building stock while fully addressing the mitigation measures [10], which requires a higher level of detail [42] to represent the building stock composition regarding building systems and ECMs [43]. In addition, the capability of the BSEM to produce models that represent short-term changes in building stock energy consumption and CO_2 emissions has not been clarified.

To fill the research gaps, this study aims to develop a BSEM framework capable of modeling short-term building stock dynamics and resultant reductions and to verify it through a case study on Japanese commercial building stock by addressing the following questions: Q1) How has the building stock changed and how much will it change by 2030, the target year for the medium-term reduction target? Q2) What are the current reductions in energy consumption and CO_2 emissions and how much would these be reduced by the target year? Q3) If a reduction gap exists in achieving the medium-term reduction target, how should this gap be filled?

This study contributes to the literature in two ways. First, we established a BSEM framework to enhance the level of detail by considering building systems and ECMs to represent the building stock dynamics and resultant reductions. Through comparison with the results of a top-down econometric analysis, we also verified that the framework can produce models for short-term changes. Second, we demonstrate the analytical capabilities of the established BSEM framework for estimating the contribution of mitigation measures and identifying the need for further policy efforts. The established framework can be applied to other regions by adjusting the input data and modeling methods. Thus, it promotes the use of the BSEM for policy assessment and evidence-based policymaking for climate change mitigation [44].

1.3. Structure of the paper

Section 2 describes the proposed BSEM framework. Section 3 presents the results of the case study, followed by a discussion in Section 4 and the conclusions in Section 5.

2. Methods

2.1. Proposed BSEM framework

Fig. 1 presents the proposed BSEM framework. The framework consists of (i) a top-down building stock decomposition process considering the annual change in building stock composition, including building systems and ECMs, and (ii) a bottom-up physics-based energy demand quantification process using RBMs. This framework is based on the method developed by Yamaguchi et al. [14]. The model is in the Q4 (bottom-up white box) quadrant of the classification by Langevin et al. [9].

The top-down decomposition begins with the total floor area (TFA) given for the target building stock, which is process (a) in the figure. In process (b), the TFA is categorized according to the basic building characteristics $\boldsymbol{x}$ (e.g., the building usage, size, and construction period) denoted as y_j for the stock segment j (= 1 to J). Then, in process (c), y_j is further decomposed according to the building systems and ECMs. In this process, the selection probabilities of the alternative k for technology i are quantified as $p_{i,k}(\boldsymbol{x}_j)$, considering the variation due to $\boldsymbol{x}$, where $\boldsymbol{x}_j$ is the average for the stock segment j. The TFA of the stock segment, TFA_m, is given as $y_j \bullet p_{i,k}(\boldsymbol{x}_j)$. The annual change in the building stock composition is expressed by considering the periods of construction and renovation in $\boldsymbol{x}$, because the change in technology adoption is transferred to the building stock composition through $p_{i,k}(\boldsymbol{x})$.

In the figure, the basic building characteristics x_1 and x_2 and

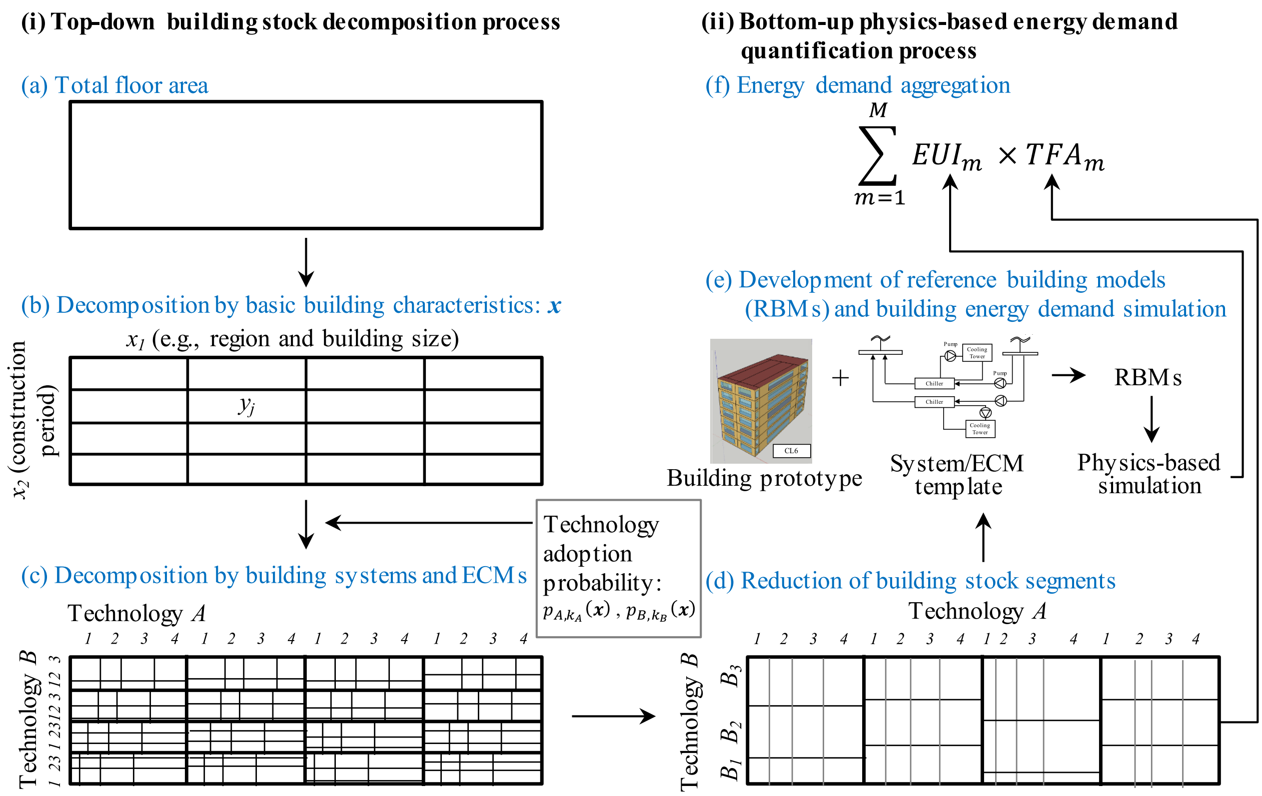

Fig. 1. Overview of the proposed BSEM framework.

technologies A and B are considered. x_2 denotes the construction period. $p_{i,k}(\boldsymbol{x})$ can be modeled using scenarios, distributions given by the sample data, and statistical and machine learning methods. $p_{i,k}(\boldsymbol{x})$ can be quantified for several technologies independently and TFA_m is given by the joint probability $y_j \bullet p_{A,k_A}(\boldsymbol{x}_j) \bullet p_{B,k_B}(\boldsymbol{x}_j)$, which is illustrated in the figure. To consider various building system types and ECMs, a combination of technologies can be considered as the alternative k (e.g., ventilation-related ECMs [14]). To consider the dependency on the adoption of other system alternatives, a variable representing the adoption can be added to $\boldsymbol{x}$ in $p_{i,k}(\boldsymbol{x})$.

In bottom-up physics-based energy demand quantification, the RBMs are developed for all building stock segments m, as shown in process (e). In the development of the RBMs, building prototypes [32] were first developed for each building stock segment j, which were used to develop the RBMs by integrating the templates of the building systems and ECMs [14]. A physics-based simulation is performed with the RBMs to quantify the EUI_m. Finally, in process (f), the total energy consumption of the building stock is quantified as $\sum_{m=1}^{M} EUI_m \times TFA_m$.

It is useful to combine several building stock segments to limit the number of RBMs in process (d). In the figure, the stock segments with different construction periods x_2 are combined into segments with the same combination of technologies A and B. This is applicable when there are no physical differences in the RBM between the different construction periods. In addition, TFA_m of some combinations may be too small to model their EUI_m. In this case, the stock segments with TFA_m smaller than a threshold value can be combined with other similar building stock segments [14].

The proposed framework enables the consideration of a higher level of detail in building systems and ECMs than the conventional BSEM methods. In most conventional methods, the building stock is classified according to only the basic building characteristics and a typical combination of the building systems and ECMs is applied. In models that consider several system alternatives (e.g., electricity/fuel-driven HVAC systems), the number of alternatives is generally small. In models that use cost optimization to select technologies for adoption, optimization is performed for the segments of the basic building characteristics, and it is difficult to represent the short-term stock dynamics. In the proposed framework, the number of RBMs is much larger than that of conventional models [45], which facilitates the representation of the heterogeneity in building stock, short-term stock dynamics, and baseline development, as demonstrated in this study.

2.2. Context of the case study

The BSEM framework was verified using a Japanese commercial building stock to address the three questions listed in the Introduction. The model covers the office, hotel, medical, retail, school, restaurant, logistics, telecommunications, and amusement building stocks, equivalent to 93 % of the 1850 million m^2 of the TFA of commercial building stocks in 2013 [46]. The 2030 reduction target for commercial building stock, assigned in Japan's Nationally Determined Contribution (NDC) [47], is 121 MtCO$_2$, which is 51 % of 238 MtCO$_2$ in 2013, including reductions from the electricity carbon intensity improvements shown in Table A2. The Japanese Plan for Global Warming Countermeasures (PGWC) [48] describes the plan to achieve the reduction target. Appendix A lists the mitigation measures and their contribution listed in the PGWC. The government also estimated the reduction progress from 2013 to 2021. This study used the reductions estimated by the government as a reference (Table A1). The potential reductions were quantified as $\sum_{m=1}^{M} \Delta EUI_m \times \Delta N_m$, as mentioned above [49]. This result may be inaccurate because ΔEUI_m and ΔN_m are modeled in a simple manner [14]. Additionally, the contributions of specific technologies are not specified for building energy efficiency improvement, except for lighting and water heating, as listed in Table A1. The promotion of heat source electrification is described in PGWC for water heating systems as the dissemination of heat pump water heater. However, it is not explicitly described for HVAC systems, although the proportion of electricity-driven systems has slowly increased [14].

The national general energy statistics [50] summarize the final energy consumption in the commercial building sector. As the statistics quantify the energy consumption using industrial classification, industrial categories were allocated to the building subsectors, as explained in Appendix B.

2.3. Top-down building stock decomposition process

Fig. 2 shows the procedure of the top-down building stock decomposition process applied in this study. We considered the basic building characteristics and the building system and ECM alternatives listed in Table 2 for the decomposition. Table 3 lists the stock segments by building size and business category.

The TFA of subsector, TFA_{Total}, was first decomposed in Eq. (1) by the basic building characteristics shown in the subscript.

$$TFA_{SS,Pref,CP|RP} = TFA_{Total} \times Prop_{SS,Pref} \times Prop_{CP|RP} \tag{1}$$

$Prop_{SS,Pref}$ and $Prop_{CP|RP}$ indicate the proportions of building stock by factors indicated in the subscript. The decomposition by basic building characteristics allows for consideration of variations in technology adoption across building stock segments. We considered the stock segments for the building size and business category in each subsector (Table 3), denoted by SS, building location represented by prefecture, $Pref$, and segments by building construction or system renovation periods, $CP|RP$, because these characteristics significantly affect technology adoption and selection probabilities. The consideration of construction and renovation periods is particularly important in representing annual changes in the building stock composition for technology adoption. The decomposition also allows for consideration of EUI variations among building stock segments, which contributes to improved model performance.

Alternative selection probabilities for lighting, insulation, combination of HVAC system types and related ECMs, COP of HVAC heat source, and water heating system type were quantified, denoted as P_L, P_I, P_HVAC, P_COP, and P_WH. The variation in these probabilities from the basic building characteristics was considered in the quantification. Then, the TFA using each combination of the technology alternatives was quantified by Eq. (2):

$$TFA_{SS,Pref,L,I,HVAC,COP} = TFA_{SS,Pref,CP|RP} \times P\_L \times P\_I \times P\_HVAC \times P\_COP \tag{2}$$

In the bottom-up demand quantification process, we considered ten regions listed in Table C1 by combining prefectures in each region. Thus, the TFA of each stock segment in each region with a specific combination of building systems and ECM alternatives was quantified in Eq. (3).

$$TFA_{SS,Region,L,I,HVAC,COP} = \sum_{Prefs\ in\ Region} TFA_{SS,Pref,L,I,HVAC,COP} \tag{3}$$

Note that P_WH was not considered in Eq (2) because we assumed that P_WH is independent from other building systems. After combining building stock segments with small TFA with others in step (d) in Fig. 1, an RBM was constructed in step (e). To consider the variation in the water heating system, a water heating system was randomly assigned to each RBM based on P_WH to reduce the number of combinations to be considered.

For the other four subsectors, we only considered typical system type and ECM combinations because available sample building data for developing statistical models of P_HVAC and P_WH was limited. Thus, the decomposition was simplified as shown in Eqs. (4) and (5).

$$TFA_{SS,Region,CP|RP} = TFA_{SS} \times \left(\sum\nolimits_{Prefs\ in\ Region} Prop_{SS,Pref}\right) \times Prop_{CP|RP} \tag{4}$$

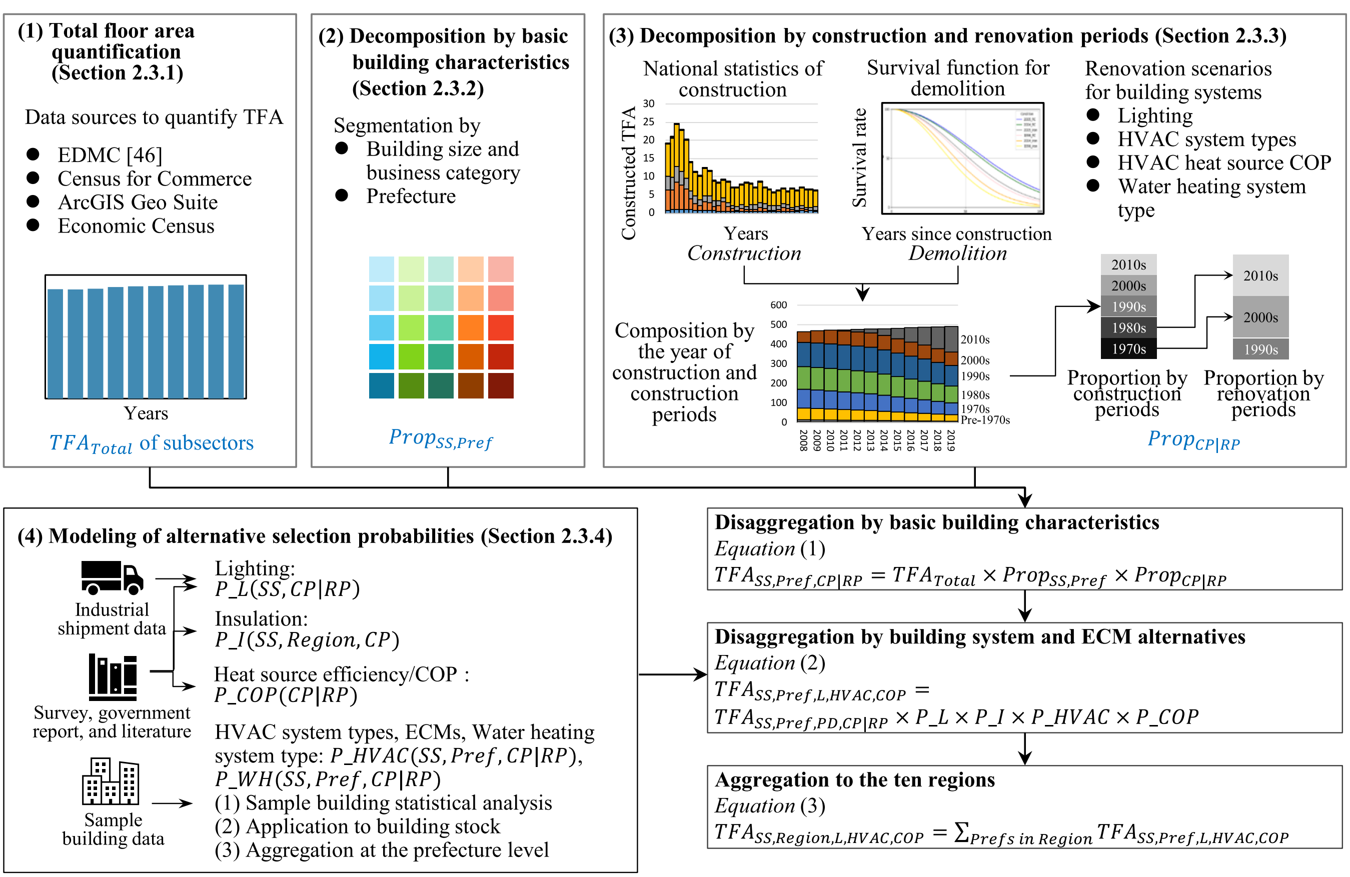

Fig. 2. Procedure of the top-down building stock decomposition.

Table 2
Items used to develop building stock segment [14].

Category	Segmentation item	Segment
Basic building characteristics	Building subsector	Office, hotel, medical, retail, school, restaurant, logistics, telecommunication, and amusement building stocks
	Prefecture and region	Classified by 47 prefectures that are summarized into ten regions, as shown in Table C1
	Building size and business category	For the office, hotel, and medical building stocks, nine building sizes, shown in Table C2 were considered. Four sizes are considered for the telecommunication building stock. Twenty-six business categories were considered for the other building stocks: 14 for retail, 3 for school, 5 for restaurant, 1 for logistics, and 3 for amusement building stocks. See Table 3 for more detail.
	Construction and renovation periods	Construction and renovation periods quantified at yearly resolution and summarized for the four construction periods, namely pre-1990 s, 1990 s, 2000 s, and 2010 and beyond.
Building system and ECM alternatives	Lighting	Conventional lighting device and light-emitting diode (LED)
	Building insulation	Eight segments are considered for building insulation performance listed in Table C5.
	HVAC system	Combinations between the configurations of the heat source system (Table C3) and the air-conditioning system (Table C4) were considered.
	Adopted HVAC-related ECMs	Sixteen segments in Table C5.
	COP of HVAC heat source	Four segments are considered for the coefficient of performance (COP) of the heat source machine of the HVAC system (Table C6).
	Water heating system	Twelve segments listed in Table C7.

$$TFA_{SS,Region,L,I,COP} = TFA_{SS,RegionCP|RP} \times P\_L \times P\_I \times P\_COP \tag{5}$$

The following subsections explain the details of the quantification method of TFA_{Total}, $Prop_{SS,Pref}$, $Prop_{CP|RP}$, and the alternative selection probabilities.

2.3.1. Total floor area quantification

Fig. 3 shows TFA_{Total} of the nine building subsectors. The third column of Table 3 lists the data sources used to quantify TFA_{Total}. The building TFA estimated by the Institute of Energy Economics, Japan [46], was used as TFA_{Total} of the office, hotel, medical, school, and restaurant subsectors, as in the PGWC. For the retail building stock, the Japanese Census for Commerce [51] containing the sales floor area of the business categories for all prefectures was used. For the logistics building stock, the sum of the TFA of warehousing and wholesale trade was used. The results for warehousing were calculated, whereas that for wholesale trade was obtained by subtracting the value for retail TFA from the TFA of retail and wholesale in [46]. The telecommunication building stock was quantified based on ArcGIS Geo Suite [53]. TFA_{Total} of the amusement subsector was unavailable. Therefore, it was quantified as the product of the average floor space of each business category and the number of establishments given in the economic census [54].

2.3.2. Decomposition by basic building characteristics

$Prop_{SS,Pref}$ was quantified by using the data listed in the fourth column of Table 3. The data sources are available for the segments made by building stock segment and prefecture, whereas Esri ArcGIS data [53]

Table 3
Building stock segment according to building size and business category.

Building usage	Segment	Data source of TFA_{Total}	Data source for segmentation
Office	Nine segments (CL1 to CL9 in Table C2)	[46]	[52]
Hotel	Eleven segments including 7 for business hotels (CL1 to CL7) and 4 for city or resort hotels (CL6 to CL9)	[46]	[52]
Medical	Nine segments (CL1 to CL9)	[46]	[53]
Retail	Fourteen business categories were considered: (1) Convenience store, (2) Housing and clothing supermarket, (3)–(5) Food supermarket (three segments considering building size: small < 1,000 m^2, medium 1,000–3,000 m^2, and large ≥ 3,000 m^2), (6), (7) Drugstore (two segments considering building size: small drugstore < 1,000 m^2 and super drugstore ≥ 1,000 m^2), (8) Home center, (9) Specialty shop, (10)–(12) General merchandise store (small < 10,000 m^2, medium 10,000–30,000 m^2, and large ≥ 30,000 m^2), and (13), (14) Department store (medium store < 30,000 m^2 and large store ≥ 30,000 m^2).	[51]	[51]
School	Primary, secondary, and high schools	[46]	[53]
Restaurant	Five business categories were considered. Brasserie/bar: Eating and drinking place open in the evening until midnight. Coffee shop/café: Drinking place open from before 10:00 a.m. until nighttime. Bistro/noodle shop: Restaurants that are open from noon to night, including those serving noodle-based dishes: BBQ restaurant Restaurants that are open from noon to night and have a stove in the seating area Other restaurants: Restaurants open from noon to night and using a gas range (gas range, low range, or Chinese range) in the kitchen.	[46]	[54]
Telecommunication	Four segments: (1) Smaller than 300 m^2, (2) 300–2,000 m^2, (3) 2,000–10,000 m^2, and (4) 10,000 m^2 or larger	[53]	[53]
Logistics	One category for warehousing and wholesaling combined	[46,53]	[54]
Amusement	Pachinko halls, fitness clubs, and karaoke boxes	[54]	[54]

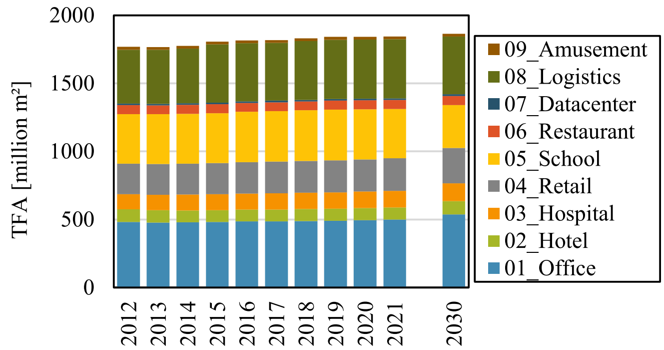

Fig. 3. TFAs of building subsectors.

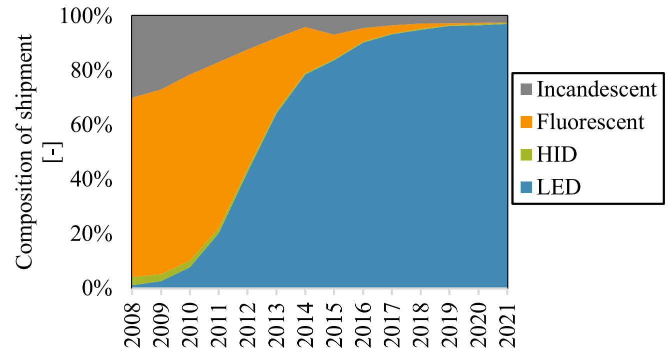

Fig. 4. Proportion of lighting fixtures and adoption probability of LED. HID: High-intensity discharge.

used for the medical, school, and telecommunications were available at the building level and $Prop_{SS,Pref}$ was quantified by summarizing individual buildings data.

2.3.3. Decomposition by construction and renovation periods

To model $Prop_{CP|RP}$, the proportion was first quantified for the year of construction by considering the balance between new construction and demolition at the yearly resolution. TFAs of new construction were given by the national statistics for new constructions [55], whereas demolition of the constructed building stock was modeled by the survival functions represented as a Weibull distribution with the Weibull parameters given by Omi et al. [56] (Section (3) in Fig. 2).

The yearly resolution TFA composition was updated considering the occurrence of renovation after the construction modelled by renovation scenarios applied to each building system. The lighting system is generally replaced every 20 to 25 years in Japan. However, it can also be replaced when interior design is changed, which increases the chance to install LED lighting systems and creates variation in renewal opportunities among building subsectors as the renovation cycle is shorter among buildings designed to attract customers. We assumed that a lighting renewal opportunity occurred once every 20 years for the office and medical subsectors, every 25 years for the school subsector, and every 15 years for the other subsectors after construction, so that the estimated adoption proportion in the stock was fitted with the variation reported in [57].

For HVAC and water heating systems, large-scale refurbishments are generally conducted with a cycle of 20 to 40 years, whereas system components are replaced every 15 to 20 years [58]. Due to the average lifetime being approximately 50 years given in the Weibull parameters in Omi et al. [56], we assumed that large-scale refurbishments were conducted once after 25 years of construction, i.e., once in the building lifetime. For the HVAC heat source machines, the renewal opportunity was assumed to be 15 years.

For the modeling of P_I, P_HVAC, and P_WH, the yearly resolution TFA composition was classified by the four construction periods to quantify $Prop_{CP|RP}$, namely pre-1990 s, 1990 s, 2000 s, and 2010 and beyond. For the modeling of P_L, P_COP, $Prop_{CP|RP}$ was quantified at the yearly resolution.

2.3.4. Application of technology selection probability to decompose TFA by building system and ECM alternatives

(1) Lighting

P_L was quantified according to the voluntary statistics summarizing the lighting fixture shipments [59,60] and applied to new construction and renovation. Fig. 4 illustrates these proportions. As the data corresponded to the period between 2008 and 2021, P_L of LED was assumed to be 0 % before 2008 and 100 % after 2021.

(2) Building insulation

For the insulation performance of the building stock, we considered four segments, namely, levels 1–4, combining the insulation of the exterior walls and windows (see Table C5). P_I was determined based on government reports according to the building construction period [6162] as shown in Fig. 5. The variation was considered for the segments according to the region (cold regions, i.e., Hokkaido and Tohoku regions, or other types of regions) and three building sizes.

(3) HVAC system type and ECMs

For the heat source, air-conditioning systems, and HVAC-related ECMs of the office, hotel, medical, retail, and school subsectors, alternative selection probabilities were quantified using logistic regression models developed based on sample data considering the building size, heating degree days (HHDs) given for 47 prefectures, population density, and construction or renovation periods as predictors. The model development and validation are explained in Yamaguchi et al. [63]. The construction and renovation periods were considered as four binary variables representing the construction and renovation periods of the pre-1990 s, 1990 s, 2000 s, and 2010 and beyond. We assumed that renovations would not change the heat source systems from a decentralized system to a centralized system, or vice versa. The adoption of technologies from 2010 followed the deployment tendency observed between 2010 and 2021, when the latest sample data were available. The logistic regression models of air-conditioning systems and ECMs also considered the distinction between centralized and decentralized HVAC systems as a predictor. For the logistics, telecommunication, and amusement subsectors, we considered Ele-VRF and HEX as the typical HVAC system type and ECM combination. In the restaurant subsector, we assumed Ele-VRF but considered various combinations of ECMs based on the same regression model developed for the retail subsector.

For the coefficient of performance (COP) of the HVAC system heat source, we considered four levels, Levels 1 to 4, representing the installation periods to address the technological development efforts of the manufacturers. Table C6 lists the average rated COP, and Fig. 6

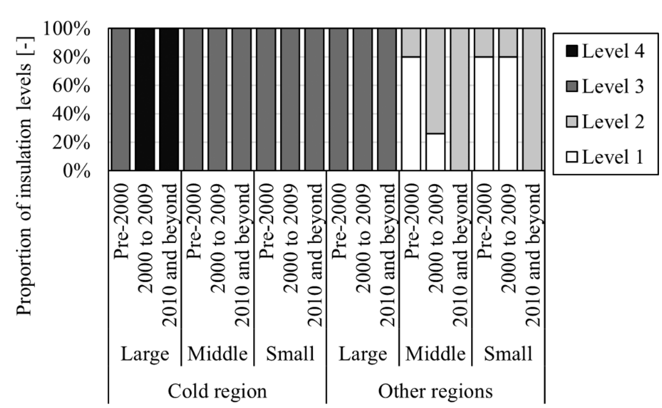

Fig. 5. Proportion of insulation levels in different construction periods: Large, Middle, and Small indicate the building size range, as follows: TFA ≥ 20,000 m², 20,000 > TFA ≥ 2,000 m², and TFA < 2,000, respectively.

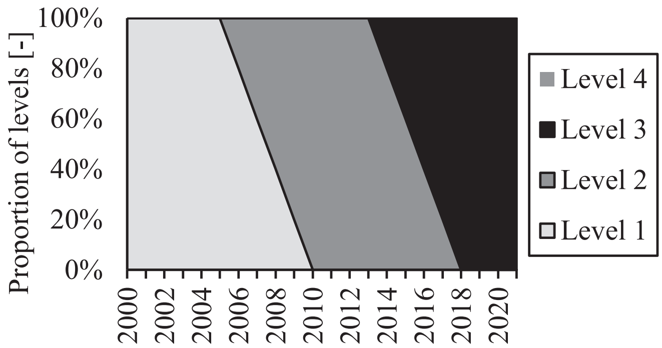

Fig. 6. Proportion of levels for rated COP of heat source machine.

shows *P_COP*. Level 3 is the average COP of new buildings in 2018, as reported by the National Institute for Land and Infrastructure Management [64]. Levels 1 and 2 were determined based on previous technical reports [14]. In addition to the rated COP, improvements in the specifications of the heat source machines were modeled. Level 4 was used to estimate the technical reduction potential using the best available technologies (see Section 2.5.2).

(4) Water heating system

The same approach as applied to the HVAC systems was applied to quantify *P_WH* for of the office, hotel, medical, retail, and school subsectors. The heat pump (HP) water heater was considered in the modeling, as it was included in the sample building data used for regression. However, the data for condensing boilers were not available in the sample dataset. Therefore, we first obtained the proportion of newly constructed or refurbished buildings in 2018 [65] and the changes in the adoption ratio over time were adjusted based on the shipment volume of condensing boilers in all gas/oil-driven boilers in the manufacturing statistics [66]. Gas/oil-driven boiler was assumed for the restaurant subsector, whereas water heating demand was not considered for the logistics, telecommunication, and amusement subsectors.

2.4. Bottom-up quantification of building energy demand

Building stock segments have been constructed based on the basic building characteristics, building systems, and ECM alternatives. The construction and renovation periods did not change the conditions represented by the RBMs. Therefore, the building stock segments differentiated by these elements were first combined. Then, those with a TFA smaller than 100,000 m^2 were combined with other stock segments following the procedure established in [14] (see Appendix D). The following improvement was added for the office, hotel, and medical subsectors if a segment was larger than 200,000 m^2: the segment was divided into the number of segments calculated as the rounded down value of $TFA_m/200{,}000\ m^2$ to limit the TFA represented by an RBM, as the energy demand quantification contains a stochastic process in the occupancy schedule. After this process, 23,244 RBMs were developed for the year 2013, excluding water heating system alternatives.

The methods in [14] were applied to develop RBMs and to perform the physics-based simulation. Appendix E presents the specifications of the building prototypes. The energy demand of RBMs was quantified using EnergyPlus ver. 8.6 [67] at time intervals of 30 min. After performing simulations, the estimated demand was normalized as the energy use intensity (EUI) per total floor area of the RBMs, and the energy consumption of each building stock segment was determined as the product between EUI and total floor area of the considered segment. For the office, hotel, and medical subsectors, the occupancy schedule of individual building users was stochastically generated to replicate the on–off conditions of building facilities [35]. For the other subsectors, the operation conditions of RBMs are given by the literature [68].

2.5. Evaluation of model estimates

2.5.1. Validation of the model

Yamaguchi et al. [14] presented a validation at the building level, showing that the energy consumption estimated using the developed RBMs fitted well with the distributions of the empirical data. Thus, in this study, a comparison was performed only with the national general energy statistics explained in Appendix B.

In addition, we validated the model by comparing the estimated reductions achieved by the energy efficiency improvements with those derived from the national general energy statistics [50]. Index decomposition analysis (IDA) [69] and the additive decomposition method of Logarithmic Mean Divisia Index I (LMDI-I) [69] were used to decompose the national general energy consumption into the changes induced by energy efficiency and TFA increase. Appendix F describes the decomposition method applied to the national general energy statistics.

2.5.2. Policy assessment

For short-term policy assessment, we quantified the reduction in the final energy consumption from the fiscal year 2013 to 2021, attributed to the mitigation measures, and compared them with those estimated by the government. To eliminate the effects of the differences in the meteorological conditions and social activities on the building stock, we prepared two sets of results. One was calculated using the stock, calendar, and meteorological conditions estimated or observed in the individual years. The other was calculated with the stock for the years and calendar and meteorological conditions in 2013. The second dataset was used to quantify the reduction resulting from the energy efficiency improvement. In addition, we evaluated the feasibility of achieving the 2030 medium-term target using the calendar and meteorological conditions in 2013. However, this calculation did not consider the effect of the COVID-19 pandemic, including the increase in teleworking and food delivery services.

Additional reductions based on the available technologies were examined to explore their reduction potential. Table 4 lists the measures used in this study.

3. Results

3.1. Building stock composition

3.1.1. LED and insulation

Fig. 7 shows the estimated building stock composition during the study period according to the construction period. The proportion of building stock constructed in the 2010 and beyond increased constantly, whereas that constructed in the pre-1990 decreased.

Table 4
Additional reduction measures.

Measures	Remarks
Best available technologies (BATs)	Level 4 of COP in Table C6 was used for all buildings.
Electrification of heat sources of HVAC and water heating systems	All HVAC heat source systems were replaced with those driven by electricity. For the decentralized system, Ele-VRF was assumed, whereas AirS-HP and AirS-HPS were assumed for the centralized HVAC system [14]. For the water-heating system, all systems except the decentralized electric water heater were replaced with an HP driven system [14].
Comprehensive ECM utilization	All ECMs listed in Tables C.5 were installed, except that for insulation performance improvement.
Insulation	Level 4 of insulation conditions in Table C5 was used in all buildings.
Assessment of potential reduction	All measures were applied to quantify the potential reduction.

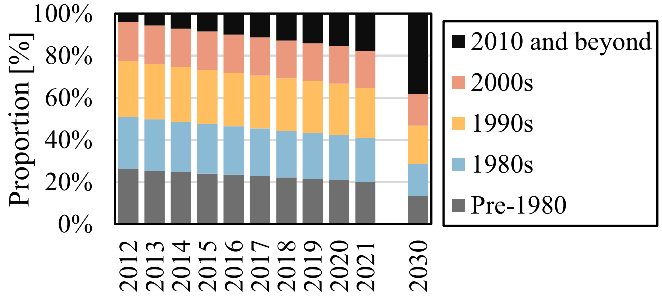

Fig. 7. Building stock composition according to construction period.

Fig. 8 shows the composition of the building stock classified according to lighting and building insulation alternatives. The use of LED was estimated to rise to 46 % by 2021 from 8 % in 2012 in the building stock. Fig. 8(a) shows the variation in the renovation opportunity cycles of 15, 20, and 25 years, as explained in Section 2.3.3. With a 15-year cycle applied to the retail and restaurant subsectors, rapid dissemination was estimated, as the adoption rate increased to approximately 60 % in 2021 and is expected to reach 97 % in 2030. In contrast, with the 25-year cycle applied to the school subsector, the adoption rate was expected to be the smallest at 79 % in 2030.

As shown in Fig. 8(b), because of the decrease in the proportion of buildings constructed in the 1980 s or earlier, the proportion of Level 1 without insulation decreased from 48 % in 2013 to 42 % in 2021 and 33 % in 2030. In contrast, the proportion of Level 2 increased from 26 % in 2013 to 32 % in 2021 and 41 % in 2030. The proportion of Level 3 with wall and window insulations did not change significantly, whereas the TFAs increased because of the TFA increase shown in Fig. 3.

3.1.2. HVAC system

Fig. 9 shows the estimated compositions of the HVAC systems. Fig. 9(a) shows the estimated compositions of the rated COP levels of the heat source machine. The composition changed rapidly owing to the frequent replacement opportunities. Level 1 disappeared by 2019, whereas Level 3 increased by 30 % by 2021. In Fig. 9(b), the estimated compositions of the heat source systems are summarized based on the system configuration and the fuel type. As shown in Fig. 9(c), the proportion of the variable refrigerant flow (VRF) system, that is, decentralized HVAC system, has gradually increased, especially in middle-sized buildings [14]. The proportion of electricity-driven systems in centralized HVAC systems has increased. In the air-conditioning system shown in Fig. 9(c), the proportion of systems using OHU has decreased significantly. Fig. 9(d) shows that the proportion of buildings equipped with multiple ECMs has not changed significantly because of the increase in decentralized HVAC systems, where advanced ECMs are rarely adopted.

3.1.3. Water heating system

Fig. 10 shows the building composition by system alternatives. A notable trend is the increased use of condensing boilers to replace conventional boilers. The proportion of HP water heaters did not increase significantly, although this was assumed in the PGWC.

3.2. Total final energy consumption of the building stock

3.2.1. Final energy consumption

Fig. 11 presents the estimated final energy consumption of electricity and fuels in comparison with the national general energy statistics, indicated as “Stats,” estimated by the method described in Appendix B. The model results were estimated using the meteorological conditions observed during individual periods. The estimated electricity consumption in 2013 was smaller by 4 %, although significant differences were observed in the data for the office, medical, and school subsectors. The difference can be partially attributed to potential errors in the statistics, as described in Appendix B, the error factors described below for the fuel, and aggregation methods of the model because the distribution of the building-level EUI fitted well with the observed distribution [14].

Fuel consumption was significantly underestimated, from 110 to 210 PJ/year. This may be because of the following reasons. First, the energy statistics may include non-building-related energy consumption and estimation errors. Second, there were leaked building subsectors and end uses. For example, cogeneration systems were ignored in the model and some fuel-driven end uses, such as for melting snow/ice, washing/disinfecting in medical facilities, and end uses in each subsector (e.g., hot springs), were not considered. Moreover, some building subsegments were not considered, for example, universities were not included in educational buildings, and fuel consumption was not considered in the telecommunication, warehouse, and amusement subsectors because sample building data were not available for the subsectors.

Fig. 12 shows the changes in final energy consumption decomposed into factors causing the annual changes estimated by the model. Continuous reductions were achieved by the energy efficiency improvements for both electricity and fuel. However, the reduction was compensated by an increase driven by the increased TFA. The effect of the meteorological conditions was quantified by the difference between the estimation results obtained using the data for the individual years and for 2013 only (Section 2.5.2). As shown in the figure, the meteorological conditions were moderate, as the energy consumption from 2014 to 2020 was smaller than that in 2013. The meteorological factor was located in the positive field in the figure except for 2021.

It should be noted that this represents a change of 5 % order of magnitude out of a total of 1650 PJ/year, whereas the national general energy statistics include changes due to economic activities.[1] Thus, the data do not match completely. However, the change in the final energy generally follows the behavior of energy consumption.

3.2.2. Energy decomposition analysis

Fig. 13 shows the decomposed results for the model and national general energy statistics given by the method explained in Appendix F. There was no significant difference in the TFA factor (TFAF) owing to the increased TFA because the same TFA values were used in the model and IDA. The reductions obtained by the energy efficiency improvement (represented by the energy efficiency factor EEF) for both electricity and fuels showed similar trends between the model and IDA until 2019, that is, before the COVID-19 pandemic.

Table 5 presents the 95 % confidence intervals of the annual increase in EEF, which is represented by γ in Eq. (F.8) in Appendix F, estimated for electricity and fuel. As shown in the table, EEFM falls within the interval of EEFI (2013–2019), whereas the model's best estimate of the EEFM was slightly higher than that of the EEFI for electricity and lower for fuel. The linear equations considering the best estimates of the EEFM as γ and β in Eq. (F.8) did not show statistically significant differences from the EEFI (2013–2019) for electricity and fuel, as the linear hypothesis test showed p-values of 0.258 and 0.253.

3.3. Contribution of mitigation measures

This section quantifies the contributions of the mitigation measures and compares them with the estimation provided by the Japanese government (see Appendix A).

3.3.1. Lighting

Fig. 14 shows the reduction caused by the dissemination of LED

[1] The difference between the data for 2020 and 2021 can be attributed to the fact that the model did not consider the changes due to the COVID-19 pandemic.

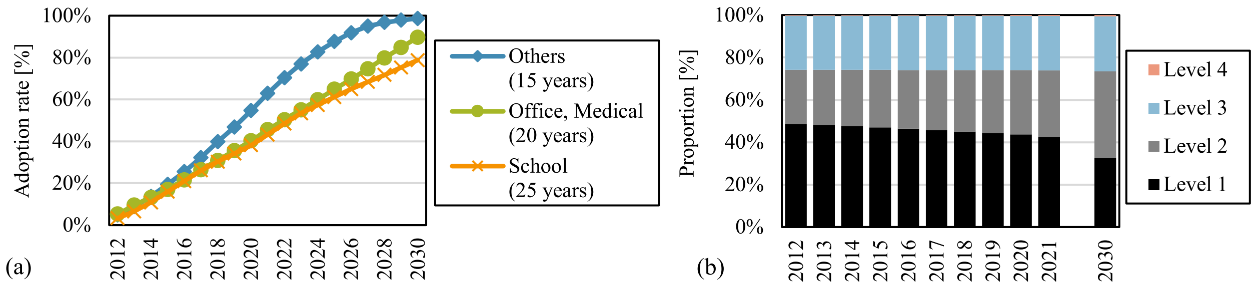

Fig. 8. (a) Estimated adoption rates of LED in building stocks with renovation opportunity cycles of 15, 20, and 25 years, and (b) those of insulation levels in the building stocks.

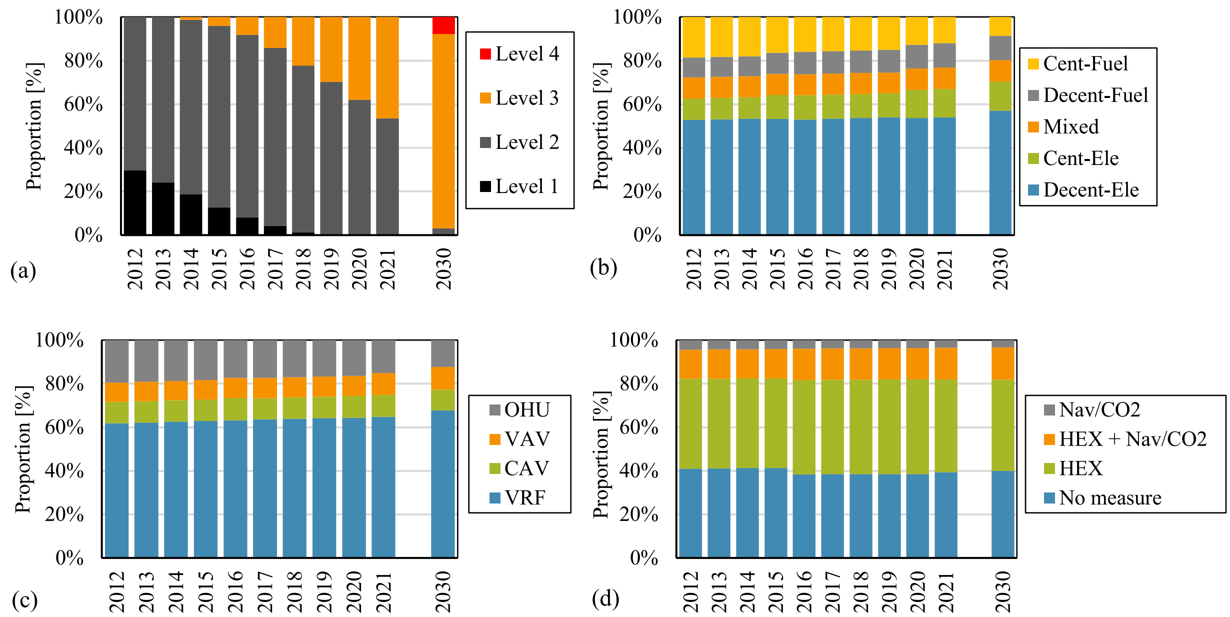

Fig. 9. Composition of building stock according to HVAC system and ECMs. (a) Levels of rated COP of heat source machine; (b) proportion of heat source systems classified as centralized (Cent) or decentralized (Decent) systems and according to the energy type of electricity (Ele) or fuel (Fuel); (c) proportion of air-conditioning systems classified as VRF and those using CAV, VAV, and OHU; and (d) proportion of ventilation-related ECMs. See Appendix C for the classifications.

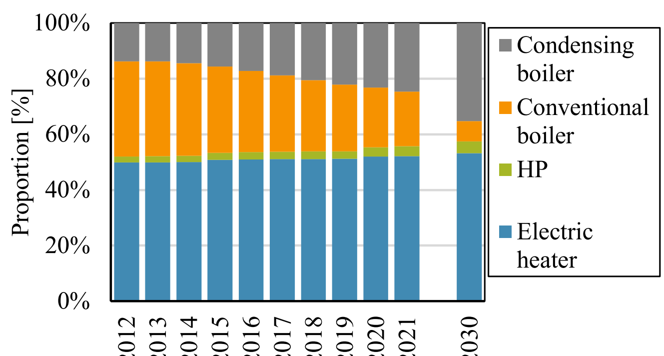

Fig. 10. Composition according to the water heating system.

lighting. Our model estimated the reduction in 2030 to be 20 PJ/year greater than the planned reduction in the PGWC. However, the model underestimated the progress until 2021 by 30 %. In the government assessment, the unit reduction was assumed to be 343.8 MJ/year per unit, with annual operating hours of 3,000 h. We confirmed that the difference is mainly attributed to the difference in operating hours, as the estimated reduction in 2030 was almost equal to that in the PGWC when the model used 3,000 operating hours with full penetration of LED, as assumed by the government. This result also implies that the government overestimated the progress of reduction because its assumed reduction per unit is smaller than that estimated by the model.

3.3.2. HVAC system

Fig. 15(a) shows the reduction for HVAC systems. The progress achieved by 2021 was greater than the government estimates. However, this fell short of the government's 2030 target by 50 PJ/year. This implies that the target cannot be achieved by extending the technology adoption trend observed between 2010 and 2021 to 2030, as assumed by the model (Section 2.3.4(3)). Fig. 15(b) shows the contributions of the changes by 2030 based on the data for 2013.[2] The largest reduction of 59 PJ/year was obtained in the system composition, which was attributed to the decentralization and electrification trend in the HVAC system heat source because the electricity consumption increases with a simultaneous decrease in fuel consumption. Note that the reduction was given as only 20 PJ/year in the primary energy consumption. The second largest decrease of 52 PJ/year was observed in the heat source efficiency, represented by the increased energy efficiency of the heat source machine, which originates from the efforts of the manufacturers. The

[2] The reduction in 2030 is larger in Fig. 15(a) than that for ALL in Fig. 15(b) because we did not consider the TFA increase to quantify the result in Fig. 15 (b).

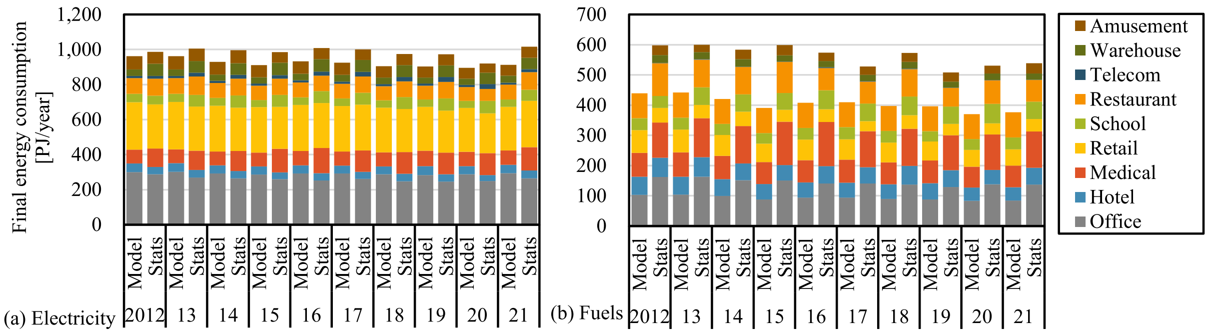

Fig. 11. Estimated final energy consumption of the building stock (Model) compared with the national general energy statistics (Stats): (a) electricity and (b) fuels.

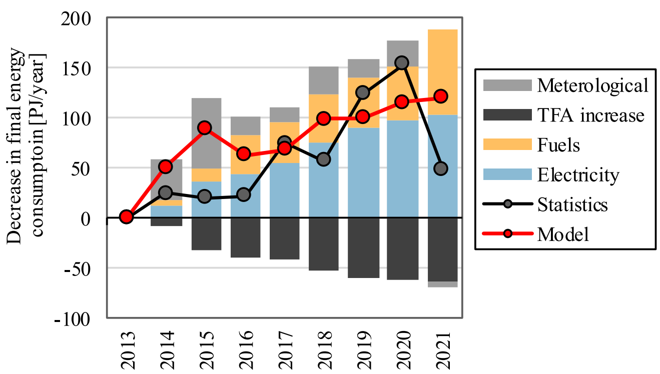

Fig. 12. Changes in the final energy consumption decomposed to those attributed to the difference in meteorological conditions, increase in TFA, and energy efficiency improvements in electricity and fuel usage.

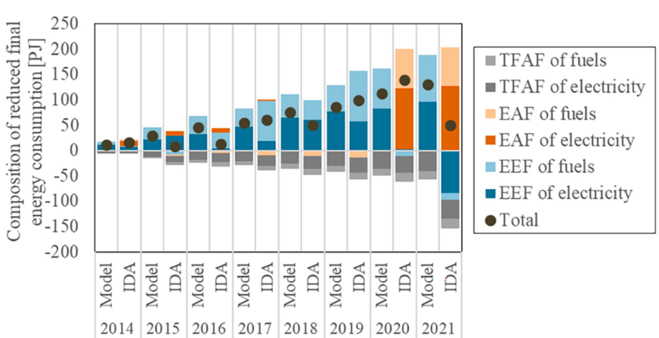

Fig. 13. Decomposition results of factors reducing the final energy consumption in comparison with the data for 2013. "IDA" indicates the disaggregated result of the statistical data by IDA; "Model" indicates the result estimated by the model. "TFAF," "EAF," and "EEF" represent the changes in TFA, economic activities, and energy efficiency causing the variation in energy consumption, respectively. See Appendix F for details.

contributions of the ECMs and insulation were relatively small. The reduced internal heat gains from improved lighting and appliance efficiency contributed to a reduction of 20 PJ/year.

3.3.3. Water heating

Fig. 16 shows the reduction in water heating. Both HP water heaters and condensing boilers were underestimated when compared with the progress assessment by the government; the deviation was larger for HP. Fig. 16(a) shows the data for condensing boilers, whereas Fig. 16(b) shows the reduction in 2030. In the model, the contribution of HP was not significant because no clear increase in deployment was observed in the sample building data used for modeling *P_WH*. As a result, 18 PJ fell short of the government target for 2030. This underestimation may be

Table 5
Confidence intervals of EEF. "EEFI" and "EEFM" represent the EEF from IDA and model, respectively.

	Electricity [PJ/year]	Fuel [PJ/year]
EEFI (2013–2021)	−4.0 ± 11.0	2.2 ± 11.1
EEFI (2013–2019)	9.5 ± 5.7	16.4 ± 8.7
EEFM (2013–2021)	12.4 ± 0.8	10.8 ± 1.7

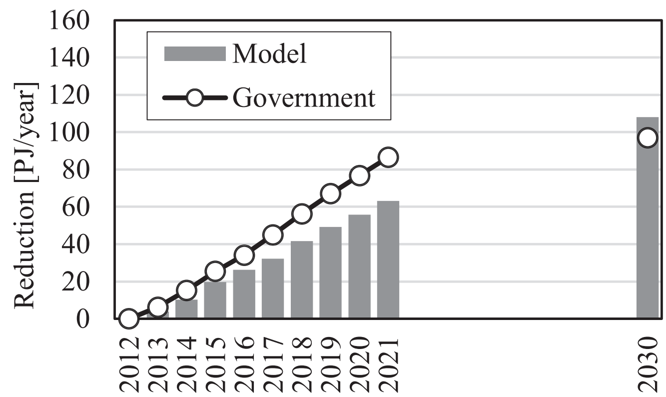

Fig. 14. Reduction in final energy for lighting.

attributed to facilities not yet considered in the model, such as hot springs and sports facilities.

The model estimated that the substitution from fuel-driven to electric water heaters has been consistently progressing in the water heating system stock. This change was estimated to deliver a reduction of 1.3 PJ/year, as indicated by "Composition" in Fig. 16(b).

3.3.4. Aggregated reduction

Fig. 17 shows the aggregated reductions achieved by the mitigation measures. Reductions in measures that were not considered in the model were given from the government estimates. The model estimates in the stacked graph were slightly larger than the government progress assessment indicated by the black line for 2021. However, in 2030, 83 PJ/year was short of the PGWC target shown in the last bar, mainly owing to the lack of reduction in HVAC (indicated as Building/HVAC) and water heating systems, as shown in the previous section.[3] Although the government estimate did not include the increased energy owing to the increased TFA, it was estimated to be 63 PJ/year in 2021, which was

[3] Energy efficiency improvement of 40% in plug-load appliances were assumed in the models for the office, hotel, medical, retail and school building stocks for the period between 2013 and 2030, as in [14]. However, it was smaller than that in the PGWC.

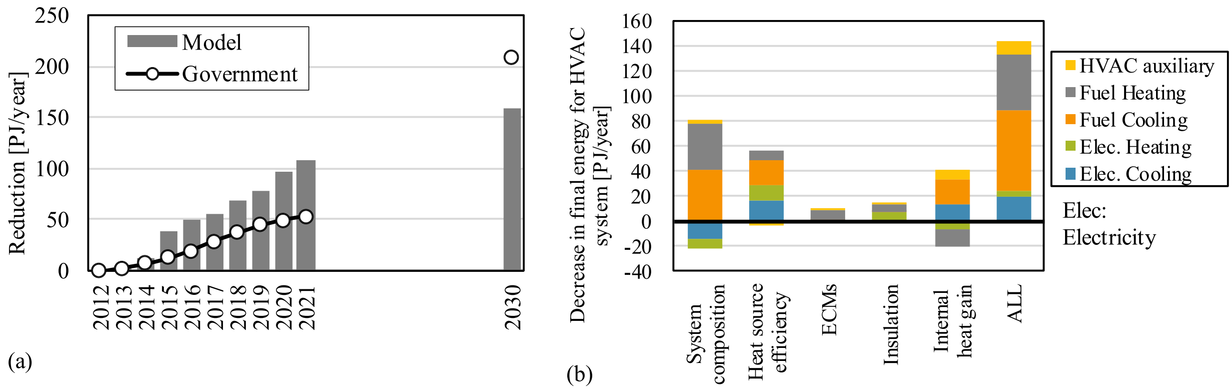

Fig. 15. Reduction in final energy for HVAC systems. (a) Total reduction and (b) components of the reduction due to the change in system composition, dissemination of ECMs, improvements in insulation, and reduction in internal heat gains. The estimated system adoption probabilities in 2030 were applied to the floor composition in 2013. ALL indicates the result with all components applied.

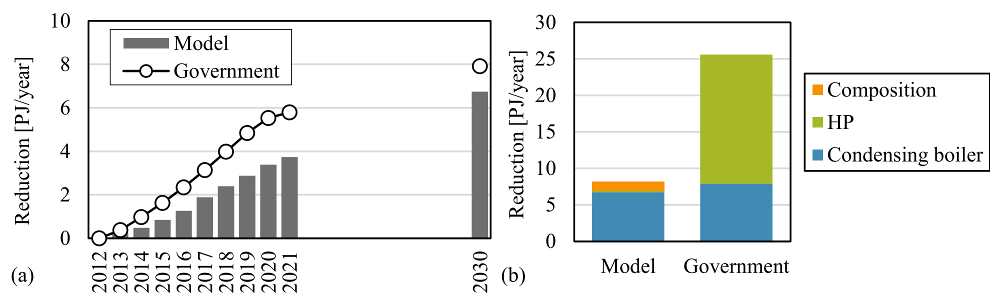

Fig. 16. Reduction in final energy for water heating systems. (a) Reduction for condensing boiler and (b) total reduction in 2030.

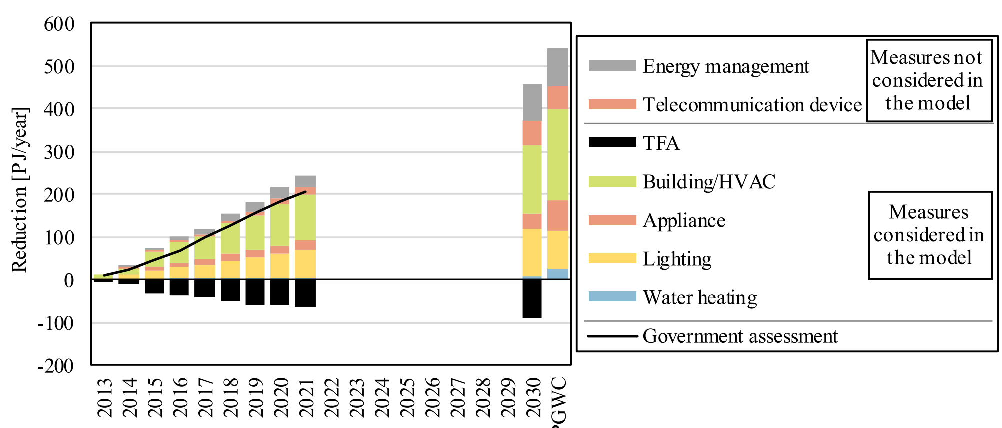

Fig. 17. Reductions aggregated for all mitigation measures.

equivalent to 31 % of the reduction estimated by the government for that year, and 91 PJ/year for 2030, which is 17 % of the target for that year. The total shortfall in 2030 was estimated to be 164 PJ/year.

In addition, the model does not consider the reduction according to energy management, but the trends of the total energy consumption are somewhat consistent, as shown in Fig. 12; therefore, it is necessary to confirm the existence of reductions due to energy management.

3.3.5. CO_2 emission reduction

In the PGWC and Japan's Nationally Determined Contribution (NDC) [47], the commercial building sector is included in "Commercial and other sectors" with the emission of 238 $MtCO_2$/year in 2013; the reduction target for 2030 is 116 $MtCO_2$/year. Fig. 18(a) shows the estimated CO_2 emissions of the building subsectors together with those of the other sectors excluded from the model analysis. Combined with the planned decrease in electricity carbon intensity from 0.57 $kgCO_2$/kWh in 2013 to 0.25 $kgCO_2$/kWh in 2030, listed in Table A2, the CO_2 emission in 2030 was estimated to be 133 $MtCO_2$/year if the energy consumption of the other sectors did not change. The shortage in the 2030 target was 17 $MtCO_2$/year. The change from 2013 to 2030 was attributed to the improvement in electricity carbon intensity (100 $MtCO_2$/year) and energy efficiency improvements in the building stock (17 $MtCO_2$/year), which was compensated by the TFA increase of 10 $MtCO_2$/year. Fig. 18(b) shows the change in the final energy consumption of the target building stock. Energy efficiency improvements decreased the total final energy consumption by 283 PJ/year, equivalent to 19 %. The proportion of electricity slightly increased from 69 % to 71 % owing to the gradual electrification of HVAC system heat sources.

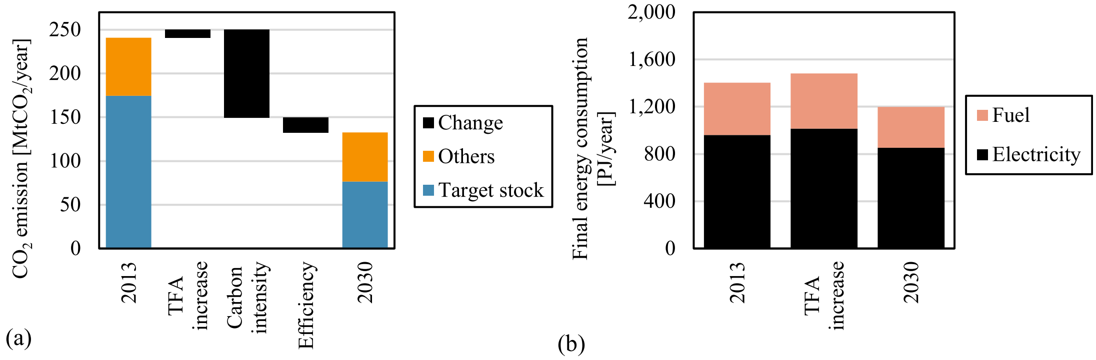

Fig. 18. (a) CO_2 emission of the target commercial building stock and other sectors indicated as "Others" and (b) final energy consumption of the target building stock.

3.4. Additional mitigation measures

Fig. 19 shows the reduction effects of the additional mitigation measures listed in Section 2.4.2 in terms of (a) final energy consumption and (b) CO_2 emissions. As shown in the potential case, the additional reductions in HVAC and water heating systems were estimated to be 243 PJ/year, which is 17 % of the total final energy consumption of the stock in 2013. This amount is greater than the total shortfall of the 2030 government target of 150 PJ/year. In terms of CO_2 emissions, the reduction potential was estimated to be 13 $MtCO_2$/year.

Regarding the decomposition, the largest reductions (116 PJ/year and 58 PJ/year) were obtained for electrification, assuming the heat source electrification in HVAC and water heating systems, which accounted for 72 % of the potential case. This reduction was larger than that for BAT (43 PJ/year), assuming the use of the best available technologies for all heat source types of Level 4 in Table C6. The improvement in building envelope insulation at Level 4 in Table C5 contributed to a reduction of 67 PJ/year. The dissemination of the available ECMs and reduction in the heat source capacity of HVAC systems contributed to a reduction of approximately 30 PJ/year. It should be noted that approximately 40 PJ/year of reduction was attributable to the HVAC system auxiliary in the electrification case because we assumed that fuel-driven centralized HVAC systems were replaced with air-source heat pumps without cooling towers.

4. Discussion

4.1. Short/medium-term reduction assessment

(1) How has the building stock changed and will it change further by 2030?

In Section 3.1, LED lighting, high-efficiency HVAC heat source machines, and condensing water heaters were estimated to be widely adopted in the building stock. These technologies are called "granular technologies" and can disseminate rapidly [70]. Compared with these measures, building envelope insulation, HVAC-related ECMs, and HP water heaters have been adopted more slowly, as a significant change in the adoption of these technologies has not been observed, or there have been fewer opportunities for their installation. However, there is a notable decentralization trend in HVAC systems. The proportion of electricity-driven HVAC systems has been increasing and is expected to increase further by 2030. However, a clear increase in the adoption of HP water heaters, which was expected by the government, was not observed in the modeled building stock.

(2) How much energy demand and CO_2 emission has been and will be reduced?

Regarding the aggregated reduction discussed in Section 3.3.4, the final energy consumption was estimated to decrease by 200 PJ/year because of the energy efficiency improvement provided by the mitigation measures between 2013 and 2021, under the same meteorological conditions observed in 2013. By including the mitigation measures that were not considered in this study, the reduction was estimated to reach 252 PJ/year. However, the reduction was compensated by 63 PJ/year owing to an increase in the TFA. The total reduction was 189 PJ/year, which was 17 PJ/year smaller than the government estimates for 2021 (205 PJ/year).

The expected reduction by 2030 by including mitigation measures not considered in this study is 468 PJ/year. By including these unconsidered measures, the deficit in the 2030 reduction target of 541 PJ/year was 164 PJ/year. As described in Section 3.3.2, the reduction in the shortages for HVAC and water heating systems mainly accounted for the aggregated shortage, together with the increased TFA. In terms of CO_2 emission, it was estimated to be reduced to 133 $MtCO_2$/year by 2030. The energy efficiency contribution was estimated at 17 $MtCO_2$/year

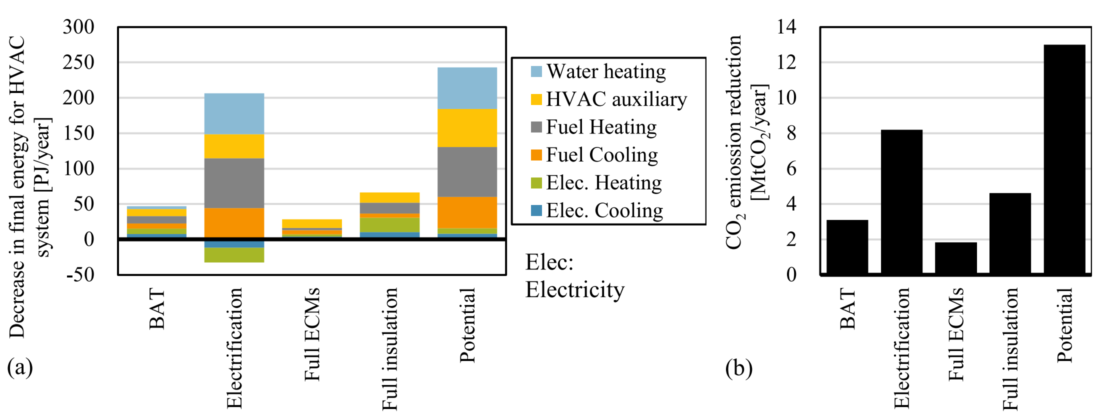

Fig. 19. Reduction obtained by the dissemination of additional mitigation measures: (a) final energy consumption and (b) CO_2 emission.

with the planned decrease in electricity carbon intensity by 2030. Note that the effects of measures not considered in this study, such as the dissemination of energy management systems, may deliver additional reductions. In the government's PGWC, the improvement in emissions attributed to telecommunication devices and building operations is 11.6 $MtCO_2$/year (see Appendix A). If these reductions are realized, the shortfall of the 2030 government target would be approximately 6 $MtCO_2$/year.

(3) How should this gap be addressed?

To overcome the shortages in meeting the 2030 targets of 164 PJ/year and 6 $MtCO_2$/year, the technology adoption trends must be modified. The results in Section 3.4 showed that the heat source electrification in HVAC and water heating systems has the largest potential for reduction, followed by improvement in the building envelope insulation performance, use of best heat source technologies, and use of available ECMs. The total potential for CO_2 emissions was estimated to be 13 $MtCO_2$/year, which is larger than the shortfall. However, the penetration speed varies depending on the installation opportunity. The insulation performance improvement takes the longest period to be realized, whereas the use of the best heat source technologies is the fastest because the lifetime of the heat source machine is generally 15–20 years and no additional system change is required. Electrification is also a fast approach but may require changes in the layout and system configuration to install electricity-driven systems.

4.2. BSEM framework

The case study demonstrated the analytical capabilities provided by the framework. The top-down building stock decomposition process enabled us to capture the state of the building stock and penetration of mitigation measures based on the available information on technology adoption, as shown in Section 3.1. The bottom-up physics-based energy demand quantification process quantifies the resultant energy and CO_2 emission reductions, including the short-term dynamics and baseline development, as shown in Sections 3.2 and 3.3. This is important for quantifying the reduction progress and avoiding overestimation. For example, the dissemination of LED will be saturated by 2030 and this strategy will not deliver further reductions. The BSEM framework quantifies the contributions of technologies by considering such realities. Furthermore, it contributes to identifying the policy gaps in the mitigation effort and, if necessary, potential reductions through additional policy efforts, as demonstrated in Section 3.4. These capabilities are useful for short-term assessments of the reduction progress and feasibility evaluations to achieve medium-/long-term reduction targets.

The results in Section 3.2 showed that the proposed BSEM framework can produce models that cover a significant part of the national general energy consumption of commercial building stock. However, the model significantly underestimated the fuel consumption when compared with the national general energy statistics (Section 3.2.1). This underestimation may be attributed to the following two reasons: first, the national general energy statistics contain non-building-related energy uses and a degree of error, as these data were estimated based on a sample survey and summarized using industrial classification, which was reorganized into the building subsectors used in this study (see Appendix B). Second, similar to other bottom-up models, leakages exist in the quantification of certain building subsectors and end uses. Section 3.2.2 showed that the annual increase in emission reduction for both electricity and fuels owing to energy efficiency improvements did not show statistically significant differences from the IDA top-down decomposition results. Based on these facts, we conclude that our model has acceptable accuracy for short-term assessment of reduction progress. In addition, it considered the key building end uses as shown in Section 3.3, which is necessary for the analysis. Therefore, the proposed BSEM framework can produce models that can estimate the short-term changes in the building stock energy consumption and CO_2 emissions.

Although the proposed framework was examined for the Japanese commercial building stock with which significant data is available for model development, the BSEM framework can be applied to other building stocks by adjusting the methods for top-down decomposition and bottom-up quantification as it is flexible in the selection of building stock data, basic building characteristics, technology alternatives, modeling methods for the adoption probabilities of the mitigation measures, design of the RBMs, and energy demand simulation using the RBMs. In this study, popular ECMs were only considered, and several important technologies and ECMs were excluded, e.g., solar photovoltaics and advanced energy management for improving building operation. The consideration requires 1) the information to assume technology dissemination, i.e. sample building data to model adoption probabilities or materials to construct dissemination scenarios, and 2) technical data to model the adoption effects in physics-based simulation with RBMs. Further research is required on how model development should be arranged according to data availability contexts so that available ECMs are fully considered.

4.3. Limitations and future works

The issues described in the previous section requires further studies. In addition, due to the lack of data showing actual conditions, verification of the estimated building stock composition in building system type and ECM was not performed. As the model was constructed based on a large number of assumptions (e.g., renovation scenarios) and available data, further study is required to establish a method for verifying estimated building stock composition and for assessing the uncertainty in model results as the building stock decomposition process and the bottom-up demand quantification process to establish a methodology to assess and assure model quality. Specifically, the developed model exhibited significant leakage in the estimated energy consumption. Additional studies are required to cover the leaked building subsectors and end uses. The existence of leakage indicates that there may be additional reductions and potential miscalculations of the reduction potential as observed in the difference in HP water heaters. Another limitation is the method of validation of national-level models. We used the results of the top-down macroeconomic analysis, which revealed that the model results do not have significant differences. However, more comprehensive validation methods should be established to validate the estimated total energy consumption and reduction effects predicted by the models, including the predictions for the subsectors and end uses.

There are three possible directions for future research. First, the BSEM framework can be extended to a national-level CO_2 emission reduction management system [44] because it can capture the state of building stock in terms of mitigation measures and CO_2 emissions, estimate baseline development, and explore alternative pathways. In addition, the framework can be extended to assess the impact of policy interventions to promote ECM adoption for better policy design. Second, energy demand data for the whole building stock would be useful for the planning and analysis of power generation and other energy supply systems and contribute to detailed integrated studies between demand and supply systems as discussed in [38] and [71]. Third, further methodological development is necessary to conduct a more comprehensive analysis of the available mitigation options, particularly for solar photovoltaics and advanced energy management. Applications of the detailed building stock modeling method on adopted technologies and ECMs to urban building energy modeling (UBEM) applied at urban levels would be useful because data acquisition methods for building systems and ECMs available for UBEM are limited [43]. However, further study is needed to enhance the spatial resolution of modeling and to acquire technology adoption data from available data sources like satellite and aerial images [72,73].

5. Conclusions

To represent the heterogeneity and short-term changes in building stock composition in terms of building systems and ECMs, this study established a building stock energy modeling (BSEM) framework that integrates top-down building stock decomposition and bottom-up energy demand quantification and is designed to achieve a higher level of detail than conventional BSEM methods. A case study on Japanese commercial building stock demonstrated the analytical capabilities delivered by the framework. The model quantified the state and change in the composition of the Japanese commercial building stock, including building systems and ECMs, the resultant reduction in energy demand and CO_2 emissions, and revealed that the stock will not achieve the 2030 reduction targets for CO_2 emissions and final energy. Additional technological changes have been explored to overcome the shortages. Although the model underestimated the fuel consumption because of errors in the national general energy statistics and leakages in capturing building subsectors and end uses, the change in final energy consumption fits well with the observations in the national general energy statistics. This result indicates that the established BSEM framework can produce models for commercial building stocks to represent short-term changes in the stock composition and the resultant reductions. The BSEM framework can be applied to other building stocks by adjusting the top-down building stock decomposition and bottom-up energy demand quantification processes. Thus, the framework promotes the use of BSEM for policy assessment and evidence-based policymaking for climate change mitigation.

CRediT authorship contribution statement

Yohei Yamaguchi: Writing – review & editing, Writing – original draft, Validation, Software, Methodology, Funding acquisition, Formal analysis, Conceptualization. **Xukang Zhang:** Writing – original draft, Validation, Methodology, Formal analysis. **Takumi Nishijima:** Writing – original draft, Validation, Software, Methodology, Formal analysis. **Yu Hayashi:** Validation, Formal analysis. **Hideaki Uchida:** Writing – review & editing, Methodology, Conceptualization. **Yoshiyuki Shimoda:** Writing – review & editing, Supervision, Resources, Project administration, Methodology, Funding acquisition, Conceptualization.

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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.

Appendix

Appendix A. .apanese plan to realize a CO_2 emission reduction target for the commercial building sector

Table A1 presents the Japanese PGWC for commercial building stocks. The estimation method is briefly explained in Section 2.2. Table A2 lists the CO_2 emission intensity of electricity used in this study. A brief explanation of the energy efficiency policy for the commercial building stock is available in [147475].

Table A1
Japanese plan to reducing the final energy and CO_2 emission of the Japanese commercial building sector.

Category	Technologies and measures to reduce CO_2 emission	Reduction in final energy consumption [PJ/year]	CO_2 emission reduction [$MtCO_2$/year]
Lighting	Diffusion of high-efficiency lighting device (i.e., LED)	91	6.7
Water heating	Diffusion of heat pump (HP) water heater and condensing boiler	25	1.4
Appliance	Improvement in appliance energy efficiency	73	4.0
	Improvement in the telecommunication device	57	5.2
Building energy efficiency	Improvement in building energy efficiency (mainly HVAC)	185	13.6
	Improvement in building operation (energy management)	88	6.4

Table A2
CO_2 emission intensity of electricity [48].

Year	Intensity [$kgCO_2$ /kWh]	Year	Intensity [$kgCO_2$ /kWh]
2013	0.570	2018	0.463
2014	0.552	2019	0.444
2015	0.531	2020	0.441
2016	0.516	2021	0.436
2017	0.496	2030	0.250

Appendix B. Quantification of energy consumption of building subsectors based on the national general energy statistics

To quantify the energy consumption of the building subsectors, we used the national general energy statistics [50] that quantify the energy consumption of industries classified based on the Japan Standard Industrial Classification. As the classification did not match our building subsectors, we mapped the industrial classifications to the building subsectors, as listed in Table B1. This study considered nine building subsectors from offices to amusement centers. The segment "Excluded" was not considered although it is included in the commercial building sector. The segment "Others" comprises sectors not included in the commercial building sector.

Table B1
Industrial subsectors allocated to the building subsectors.

Building subsectors	Corresponding industrial classification
Office	E Management department of manufacturing industry, G Information and communication industry (38–41), I Non-Store Retailers (61), J Finance and insurance industry (62–67), K Real estate and goods rental industry (68–70), L Academic research, professional and technical services industry (71–74), O Educational support industry (82), Q Combined service business (86, 87), R Other services (91–93), S Public service (excluding those classified as others) (97, 98)
Hotel	M Accommodation and food service industry (75 Accommodation)
Medical	P Medical and welfare services (83 Medical services, 84 Health and hygiene, 85 Social insurance, social welfare, and caregiving)
Retail	I Wholesale and retail trade, specifically retail (excluding wholesale, 56–60), N Life-related services and entertainment industry (78 Laundry, barber, beauty, and bath services (excluding baths))
School	O Education and learning support industry (81 School education)
Restaurant	M Accommodation and food service industry (76 Restaurants, 77 Take-out, and delivery food services)
Telecommunication	G Information and communication industry (37)
Logistics	H Transport and postal services (47), I Wholesale sector of wholesale and retail trade (50–55)
Amusement	N Life-related services and entertainment industry (80 Entertainment industry)
Excluded	N Life-related services and entertainment industry (78 Bathhouse business), 79 Other life-related services (ceremonial occasions like weddings and funerals), excluding 80 Entertainment industry, R Other services (94: Religion)
Others	F Electricity, gas, heat supply, and waterworks industry (33–36), H Transportation and postal services (42–46, 48, 49), R Other services (88–90), T Unclassifiable/estimated classification errors

It should be noted that the energy consumption of the building subsectors cannot be accurately estimated based on the data because the energy consumption of each sector was estimated using sample surveys and included the energy consumption for non-building-related activities. In addition, the energy consumption of industrial sectors may include those for different building subcategories. For example, office buildings operated by each industry are categorized. The energy consumption of the administrative section is available only for the manufacturing industry in the energy consumption statistics [76]. It was included in the office category.

Appendix C. Building system and ECM alternatives

Table C1
Categories of regions located from the North to the South.

Region	Prefecture
Hokkaido	Hokkaido
Tohoku	Aomori, Iwate, Miyagi, Akita, Yamagata, and Fukushima
Kanto	Ibaraki, Tochigi, Gunma, Saitama, Chiba, Tokyo, and Kanagawa
Hokuriku	Niigata, Toyama, Ishikawa, and Fukui
Chubu	Yamanashi, Nagano, Gifu, Shizuoka, and Aichi
Kansai	Mie, Shiga, Kyoto, Osaka, Hyogo, Nara, and Wakayama
Chugoku	Tottori, Shimane, Okayama, Hiroshima, and Yamaguchi
Shikoku	Tokushima, Kagawa, Ehime, and Kōchi
Kyushu	Fukuoka, Saga, Nagasaki, Kumamoto, Oita, Miyazaki, and Kagoshima
Okinawa	Okinawa

Table C2
Classification by building size consistently applied for office, hotel, and medical subsectors based on [52].

Segment	Range of floor area [m2]	Segment	Range of floor area [m2]
CL1	Smaller than 200	CL6	5,000–10,000
CL2	200–500	CL7	10,000–20,000
CL3	500–1,000	CL8	20,000–50,000
CL4	1,000–2,000	CL9	50,000 or larger
CL5	2,000–5,000		

Table C3
Categories of heat sources of the HVAC system.

Category		Heat source for cooling	Heat source for heating	Adoption of thermal storage
Decentralized system	Ele-VRF	Electricity-driven VRF	Same as cooling	
	Gas-VRF	Gas-driven VRF	Same as cooling	
	Mix-VRF	Both Ele-VRF and Gas-VRF	Same as cooling	

(*continued on next page*)

Table C3 (*continued*)

Category		Heat source for cooling	Heat source for heating	Adoption of thermal storage
Centralized system	AirS-HP	Air-source HP	Same as cooling	
	AirS-HPS	Air-source HP	Same as cooling	Adopted
	E-C&G-B	Electricity-driven chiller	Gas boiler	
	Gas-AbCB	Absorption chiller	Gas boiler	
	Gas-AbCH	Absorption chiller-heater	Same as cooling	
	Comb-EG	Electricity-driven chiller and absorption chiller-heater	Absorption chiller-heater	
	WaterS-CS	Electricity-driven chiller and absorption chiller-heater	Absorption chiller-heater	Adopted

Table C4
Categories of air-conditioning system.

Category		Heating and cooling	Ventilation
Decentralized system	VRF	VRF system	Ventilation system is independently installed
Centralized system	FCU	FCU	Same as VRF
	CAV	Air handling unit (AHU) with CAV control	Air intake is mixed in AHU
	VAV	AHU with VAV control	Same as CAV
	CAV + FCU	Same as in CAV but the perimeter zone is controlled by FCU	Same as CAV
	VAV + FCU	Same as CAV + FCU but VAV in AHU	Same as CAV
	OHU + FCU	FCU in both interior and perimeter zones	OHU

Table C5
Categories of combinations of ECMs. A total of 512 combinations was considered by combining the four categories except the heat source COP.

Category	Measures	Combination
Building insulation	Exterior wall insulation No insulation: U-value 1.80 W/m^2 Cold regions: U-value 0.72 W/m^2 with 30 mm rigid urethane foam Other regions: U-value 0.55 W/m^2 with 20 mm rigid urethane foam Window insulation Single glazing: U-value 5.96 W/m^2 Double glazing: U-value 3.27 W/m^2 Low-e double glazing: U-value 2.46 W/m^2	Level 1: No insulation and single glazing Level 2: Wall insulation and single glazing Level 3: Wall insulation and double glazing Level 4: Wall insulation and low-e double glazing
Lighting	Adoption of LED	LED adoption or not
Ventilation-related measures	Heat exchanger in air intake (HEX) Natural ventilation using economizer (Nav) Air-intake quantity control based on CO_2 concentration in the conditioned space that minimizes the volume of air intake, modeled using the air-intake volume per person (indicated as CO_2V)	All combinations of the three measures
Heat-delivery-related measures	VWV. VAV is modeled in the categories of the air-conditioning system (Table C4)	VWV control was adopted
COP of heat source of HVAC systems	Rated COP	Four levels listed in Table C6

Table C6
Assumed estimated annual rated COP [W/W] [14].

Heat source		Level 1	Level 2	Level 3	Level 4
Multi-function for building	Cooling	2.5	3.0	3.5	3.5
	Heating	3.1	3.5	4.0	4.3
Gas-driven heat pump	Cooling	0.9	1.0	1.2	1.4
	Heating	1.1	1.2	1.4	1.6
Air-source heat pump	Cooling	2.9	3.2	3.6	3.7
	Heating	3.1	3.3	3.6	3.7
Absorption chillers		1.0	1.1	1.3	1.6
Compression chillers		5.0	5.3	5.7	6.5

Table C7
Categories of water heating system.

Category		Fuel	Heat source
Decentralized system	WH-Dec-Ele	Electricity	Electric heater
	WH-Dec-Gas	Gas	Gas conventional boiler
	WH-Dec-Oil	Oil	Oil conventional boiler
	WH-Dec-GasC	Gas	Gas condensing boiler
	WH-Dec-OilC	Oil	Oil condensing boiler
	WH-Dec-HP	Electricity	HP water heater
Centralized system	WH-Cen-Ele	Electricity	Electric heater
	WH-Cen-Gas	Gas	Gas conventional boiler
	WH-Cen-Oil	Oil	Oil conventional boiler
	WH-Cen-GasC	Gas	Gas condensing boiler
	WH-Cen-OilC	Oil	Oil condensing boiler
	WH-Cen-HP	Electricity	HP water heater

Appendix D. Method for reducing building stock segments

The construction and renovation periods do not change the conditions represented by the RBMs. Therefore, the building stock segments differentiated by the periods were first combined. The following procedure was employed to reduce the number of building stock segments for which the RBM was developed. The threshold value Y_{TH} used in the process was 100,000 m^2.

(1) If the TFA of an HVAC heat source system for a building size and business category in a region is smaller than Y_{TH}, the TFA is redistributed among the other categories using the proportion of the TFA of the other HVAC heat source systems with TFA larger than Y_{TH}. The TFA of each combination of the air-conditioning system and ECMs is retained in this process.
(2) If the TFA of an air-conditioning system within a building size and business category in a region with a centralized HVAC heat source system is smaller than Y_{TH}, the TFA is redistributed to the other air-conditioning systems using the proportion of the TFAs with the other types of air-conditioning systems. The TFA of the ECMs with the air-conditioning system was retained during this process. The same process was conducted for the decentralized HVAC systems.
(3) If there were categories with TFA smaller than Y_{TH}, the TFAs of the combinations were redistributed among those of the other ECM categories using the proportion of TFAs with the remaining ECMs.

Appendix E. Specifications of building prototypes

The building prototypes presented in [14] were applied for the office, hotel, medical, retail, and school building stocks. For the restaurant, logistics, telecommunications, and amusement building stocks, building prototypes were newly developed. Table E1 lists the building prototypes used in this study. A building system model was integrated based on the system categories of the HVAC and water heating systems. The building prototypes were designed based on the method described in [33].

Table E1
Specifications of building prototypes.

Usage	Attributes	CL1	CL2	CL3	CL4	CL5	CL6	CL7	CL8	CL9
Office	TFA [m^2]	132	349	726	1,447	3,258	7,089	13,873	31,238	190,202
	Building coverage [m^2]	66	116	182	289	543	1,013	1,734	2,840	6,559
	Number of stores	2	3	4	5	6	7	8	11	29
	Floor composition	Office							Office, meeting room, restaurant, and retail shop	
Hotel	TFA [m^2]	137	364	744	1,444	3,200	7,611	15,083	34,528	177,850
	Building coverage [m^2]	69	121	186	289	457	846	1,160	2,877	6,587
	Number of stores	2	3	4	5	7	9	13	12	27
	Floor composition	Room clerk and lobby			Room clerk, lobby, and restaurant			Room clerk, lobby, restaurant, and banquet hall		
Medical	TFA [m^2]	136	330	701	1,455	3,238	7,597	14,696	31,309	104,835
	Building coverage [m^2]	68	110	234	364	648	1,266	2,449	4,473	6,989
	Number of stores	2	3	3	4	5	6	6	7	15
	Floor composition	Clinic, waiting room, lobby, and inspection office			Clinic, waiting room, lobby, inspection office, and bedroom		Clinic, waiting room, lobby, inspection office, bedroom, and operating room		Clinic, waiting room, lobby, operating room, intensive care unit (ICU), inspection office, and bedroom	
Retail	Fourteen building prototypes were designed for each of the 14 business categories shown in Table 3. The building prototypes comprise a sales floor area and backyard. Refrigeration facilities were considered in the business categories selling fresh food and beverages.									
School	Three building prototypes were designed for elementary, secondary, and high schools. These school buildings consisted of two buildings with three stories and floor areas of (a) 3,000 m^2 and (b) 1,500 m^2. The buildings comprised classrooms, special classrooms, and management rooms.									
Restaurant	A typical building prototype with floor area of 151 m^2 was designed. The floor was divided into backyard, kitchen, and seating areas.									
Telecommunication	Four building prototypes were designed for the four segments: (1) smaller than 300 m^2, (2) 300–2,000 m^2, (3) 2,000–10,000 m^2, and (4) 10,000 m^2 or larger. The floor plan was divided into communication equipment rooms, offices, non-air-conditioning rooms.									
Logistics	A typical building prototype was designed. The floor plan was divided into warehouse and backyard.									
Amusement	Three typical building prototypes were designed for pachinko halls, fitness clubs, and karaoke boxes.									

Appendix F. Validation method based on top-down analysis

We validated the model by comparing the estimated results with those derived from the national general energy statistics. The comparison included changes in energy consumption owing to energy efficiency improvements and increased TFA. IDA [77] and LMDI-I [78] was used to decompose the national general energy consumption into the effects of different factors.

Using the IDA variant, the total energy consumption (TEC) can be decomposed based on the economic activity index (EAI) and TFA into the following three factors: energy efficiency (EE), economic activity (EA), and TFA, as shown in Eq. (F1):

$$\mathrm{TEC} = \frac{\mathrm{TEC}}{\mathrm{EAI}} \cdot \frac{\mathrm{EAI}}{\mathrm{TFA}} \cdot \mathrm{TFA} = \mathrm{EE} \cdot \mathrm{EA} \cdot \mathrm{TFA} \tag{F1}$$

Here, we used the tertiary industry activity index [79] for the EA. In practice, the estimated TEC, $\mathrm{TEC}_{estimate}$, does not exactly match the observed TEC, $\mathrm{TEC}_{observe}$, as variations can arise owing to differences in meteorological conditions. This is referred to as the meteorological factor (MF), as shown in Eq. (F2).

$$\mathrm{TEC}_{observe} = \mathrm{TEC}_{estimate} + \mathrm{MF} = \mathrm{EE} \cdot \mathrm{EA} \cdot \mathrm{TFA} + \mathrm{MF} \tag{F2}$$

Hence, Eq. (F1) can be converted to Eq. (F3) as

$$\mathrm{TEC}_{estimate} = \mathrm{TEC}_{observe} - \mathrm{MF} = \mathrm{EE} \cdot \mathrm{EA} \cdot \mathrm{TFA}, \tag{F3}$$

where MF is obtained from the government estimation [80]. Then, the change in $\mathrm{TEC}_{estimate}$ can be disaggregated into the change due to three main factors: A) improvement in energy efficiency (EEF), B) change in economic activities (economic activity factor EAF), and C) change in the TFA (TFAF). Following the additive analysis, the LMDI-I model was used to quantify the three terms, as shown in Eq. (F.):

$$\Delta \mathrm{TEC}_t = \mathrm{TEC}_{estimate,t} - \mathrm{TEC}_{estimate,0} = \mathrm{EEF}_t + \mathrm{EAF}_t + \mathrm{TFAF}_t, \tag{F4}$$

where $\Delta\mathrm{TEC}_t$ indicates the change in TEC from the year 2013, with the year $t = 0$. We are interested in comparing the EEF with the reduction gained by the energy efficiency improvement estimated by our model. The process was applied to electricity and other fuel consumption, respectively. According to the LMDI-I, the effects of individual factors is calculated using Eqs. (F5), (F6), and (F7).

$$\mathrm{EEF}_t = \frac{\mathrm{EC}_t - \mathrm{EC}_0}{\mathrm{LnEC}_t - \mathrm{LnEC}_0} \mathrm{Ln}\left(\frac{\mathrm{EEF}_t}{\mathrm{EEF}_0}\right) \tag{F5}$$

$$\mathrm{EAF}_t = \frac{\mathrm{EC}_t - \mathrm{EC}_0}{\mathrm{LnEC}_t - \mathrm{LnEC}_0} \mathrm{Ln}\left(\frac{\mathrm{EAF}_t}{\mathrm{EAF}_0}\right) \tag{F6}$$

$$\mathrm{TFAF}_t = \frac{\mathrm{EC}_t - \mathrm{EC}_0}{\mathrm{LnEC}_t - \mathrm{LnEC}_0} \mathrm{Ln}\left(\frac{\mathrm{TFA}_t}{\mathrm{TFA}_0}\right) \tag{F7}$$

The annual trends of EEF_t values from the IDA and model were then estimated using the ordinary least squares (OLS) method and the results were compared using Eq. (F8).

$$\mathrm{EEF}_{\hat{y},t} = \gamma \cdot t + \beta, \tag{F8}$$

where $\mathrm{EEF}_{\hat{y},t}$ captures the evolving trend of energy efficiency, with γ quantifying the annual change, which is comparable with the model estimates.

Notably, our assessment periods included 2020 and 2021, which were affected by the COVID-19 pandemic. To mitigate the influence of several latent factors, we conducted IDA analysis for two distinct periods: from 2013 to 2019, and from 2013 to 2021.

Data availability

Data will be made available on request.

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