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REVIEW ARTICLE

Assessment models and dynamic variables for dynamic life cycle assessment of buildings: a review

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Abstract
Life cycle assessment (LCA) is widely used to quantify the environmental performance of buildings. Recently, the potential temporal variations in the lifetime of buildings and their influences on assessment results have attracted considerable attention. Dynamic LCA (DLCA) is an emerging research topic. This study provides an overview of the current scenario of DLCA studies in the building field. A literature survey was conducted by searching through scientific literature databases; 48 articles met the inclusion criteria. Eleven dynamic variables as well as their addressing approaches were summarized and analyzed. A few typical dynamic assessment models were synthesized and compared to present the methodology progress. Finally, considering the existing limitations, a few research directions were recommended: setting cutoff criteria for dynamic variables, developing a dynamic database, and considering the interactions between dynamic variables. The analyses in this study indicate that research on the DLCA of buildings needs interdisciplinary cooperation. This review promotes in-depth understanding about DLCA research of buildings and offers valuable implications for environmental practice. The highlighted future research directions facilitate further explorations in this research area.

Keywords Dynamic life cycle assessment · Temporal variation · Environmental impact · Building; Sustainable development

Introduction

According to the International Energy Agency, global buildings and construction activities occupy 36% of the world's energy consumption and 40% of the total CO_2 emissions (International Energy Agency 2017). Building-related greenhouse gases (GHGs) will approximately double in the next 20 years if remedial actions are not taken (Sustainable Buildings and Climate Initiative 2009). An increasing number of countries have identified the sustainable buildings as a key potential solution to global warming and energy crisis. Life cycle assessment (LCA), a systemic and objective environment management tool, has been used in the building field to quantify environmental impacts (EIs) and guide decision-making. Research on the LCA of buildings has developed rapidly, and related studies have increased significantly in recent decades (Geng et al. 2017). Some leading organizations, such as the European Committee for Standardization and the International Organization for Standardization (ISO), have established specific standards for investigating the sustainability of buildings (European Committee for Standardization 2011). A variety of LCA tools and databases for buildings have been developed at multiple scales, including product comparison tools (e.g., Building for Environmental and Economic Sustainability, SimaPro, and Life Cycle Explorer), decision support systems (e.g., Athena and Envest), and assessment tools (e.g., the Building Research Establishment assessment method).

However, traditional LCA studies exclude temporal information and aggregate activities and elementary flows at different times, which has been viewed as a significant bottleneck (Chau et al. 2015; McManus and Taylor 2015). The ISO

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states that the environmental relevance of the assessment results decreases due to missing temporal information (ISO 2000). In an assessment, the elementary flows vary with external changes (Cardellini et al. 2018; Faraca et al. 2019). Emissions at different time points have different implications for environmental damage processes and impacts (Lebailly et al. 2014; Struijs et al. 2010). In addition, environmental preferences and treatment costs may change over time (Su et al. 2019c; Zhang 2017). If these variations are neglected, the assessment results may not adequately reflect real situations, thereby risking result-based decisions and improvements (Yuan et al. 2015). Since the last decade, scholars have conducted many dynamic LCA (DLCA) studies that attempted to describe temporal variations using time-varying parameters and incorporate them into assessment. DLCA studies have been conducted in many industries and areas, such as energy (Kumar et al. 2019; Milovanoff et al. 2018), crops (Laratte et al. 2014), and vehicles (Onat et al. 2016; Walker et al. 2015). Many studies have shown that the DLCA is capable of providing more accurate, reliable, and meaningful assessment results (Breton et al. 2018; Demertzi et al. 2018). DLCA has been an emerging research topic in the international environmental management area.

Conducting a DLCA of buildings (DLCA-B) is meaningful and complex for the specifics of buildings (Mequignon et al. 2013; Su et al. 2019b). Firstly, a building has a much longer life cycle than most general products, up to many times. The potential changes over decades may be large and can sway decisions. Secondly, buildings generate large energy consumption, emissions, and EIs; hence, buildings play significant roles in reaching the energy conservation and emission reduction targets of many countries. The DLCA can offer more accurate assessment results and support timely decisions, thereby making enhanced contributions to sustainable development goals. Thirdly, buildings are a very complex application of LCA (Buyle et al. 2013; Cabeza et al. 2014). Buildings involve numerous types of materials with different lifetimes and production processes. They also consist of various activities, and they have a large diversity of stakeholders. The related temporal variations are multiple, complex, and uncertain (Breton et al. 2018). Conducting a DLCA for buildings is more difficult than that for other products. Considering the above three specifics (i.e., long life cycle, large EIs, and complex application), it is highly necessary and valuable to conduct DLCA-B research.

In the past decade, dozens of papers investigating DLCA-B have been published, and some progress has been achieved. Currently, only one related review has been published (Breton et al. 2018). However, that review was mainly devoted to comparing the methodologies of two dynamic approaches (i.e., pairing time-differentiated inventory with dynamic characterization factors and using biogenic global warming potential) to identify the more suitable one for buildings. Many potential temporal variations in the life cycle of buildings were not mentioned, and building characteristics were rarely considered. A comprehensive analysis and review are still needed to offer a holistic picture of the actual research status.

This study aims to summarize the current achievements and limitations of DLCA-B research. It makes three contributions. First, dynamic variables during the entire life cycle of a building are systematically identified, and their research progress is well presented. The addressing approaches and main data sources are synthesized. Second, some typical dynamic models for buildings are analyzed and compared to provide reference for future dynamic studies. Third, some potential future research opportunities are provided: setting cutoff criteria for dynamic variables, developing a dynamic database for buildings, and considering the interactions between dynamic variables. This review provides a foundation for future dynamic studies and could significantly contribute to building sustainability.

Method

To fulfill the aim, this review adopted the following procedures: a literature survey, screening, and analysis and summary. Figure 1 illustrates the workflow of the research method.

Literature survey

The literature survey was conducted using Scopus as the search engine. Scopus leads over many other databases by covering a wider journal range (more than 22,000 journals) (Falagas et al. 2008). It is regarded as one of the most complete databases and has been widely used to conduct systematic literature reviews (Calabrese et al. 2018; Muller et al. 2019). After selecting the database, a structured search was conducted to retrieve the literature. The LCA, temporal dynamics, and buildings were the three central topics. The following terms: “life cycle assessment” OR “life cycle analysis”

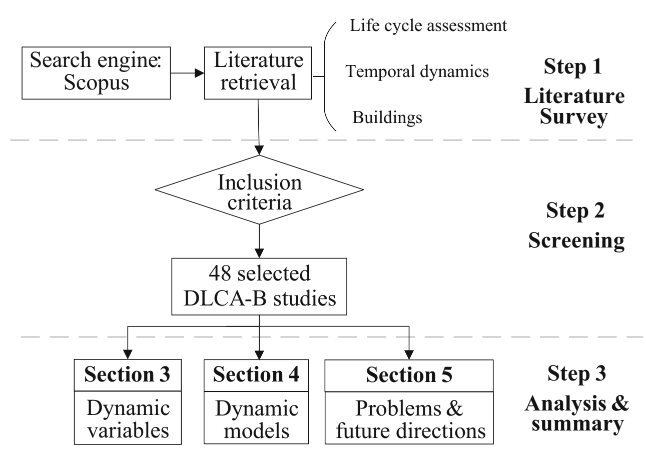


Fig. 1 Flow chart of research method for this paper

OR “LCA,” AND “time-dependent” OR “time-varying” OR “dynamic” OR “temporal,” AND “building” OR “construction” were used to retrieve papers wherein these terms were found in the title, abstract, and/or keywords. No starting point was determined for publication date, and papers that were published before the end of 2019 were retrieved.

Screening

To guarantee the relevance and eligibility of the retrieved papers, the authors carefully reviewed them on a case-by-case basis, based on the full body of text of each paper. Four inclusion criteria were defined as follows to identify relevant papers. Finally, 48 DLCA-B papers that met these inclusion criteria were selected (as summarized in Table 1).

- Language: English
- Document type: Only journal articles and conference papers
- Availability of full text: Available
- Research content: LCA of buildings with temporal variations considered

Analysis and summary

After analyzing the selected articles, the following interesting findings can be found.

- DLCA-B studies were conducted around the world and most of them were published during the last 10 years
- The assessment scopes of less than one third of these studies covered the entire life cycles
- Various time steps were used, including annual, monthly, and daily
- Nearly 70% of the DLCA-B papers were conducted prior to the construction phase or operation phase, and they belonged to pre-assessment studies

By using the selected papers, a clear report can be performed, including dynamic variables summary (“Dynamic variables” section), methodological research progress analysis (“DLCA models for buildings” section), and discussion of existing problems and future research directions (“Existing problems and future directions” section).

Dynamic variables

In DLCA studies, dynamic variables are essential and significant. Scientifically identifying dynamic variables and accurately describing their variations over time is a primary task (Negishi et al. 2018; Yang and Chen 2014). Some dynamic variables are highly associated with the assessed objects (herein buildings), and their values vary when the assessed building changes. These dynamic variables usually affect the material inputs and emission outputs of the building during its life cycle, and they are analyzed in the “Building-related dynamic variables” section. In addition, some dynamic variables are related to LCA methodology and have little relationship with buildings. Their temporal values are usually adaptive to many products. Dynamic characterization factors and dynamic weighting factors are typical examples. They are briefly introduced in the “Other dynamic variables” section.

Building-related dynamic variables

This section focuses on eight building-related dynamic variables, including occupants and behaviors, energy evolution, degradation of materials and devices, carbon absorption, expected service lives (ESLs) of components and devices, temperature change, technological evolution, and waste recycling rates.

Occupants and behaviors

Occupants and their behaviors play roles in the operational energy consumption of many buildings, and they affect assessment results. This has been well demonstrated by many studies performed in different countries (Al-Mumin et al. 2003; Lopes et al. 2005). Occupants and behaviors change over time. Some studies have dedicated significant portions of their investigations to the significance of occupants and their behaviors and viewed this aspect as a typical dynamic characteristic of DLCA-B studies (Negishi et al. 2018; Thomas et al. 2016).

Current DLCA-B studies have addressed this dynamic variable mainly in two ways. (1) Some scholars described the variations of occupants and/or behaviors over time and then quantified their influences on operational consumption. The involved dynamic data were mainly from reports and statistics. Here are some examples. Negishi et al. (2019) acquired the temporal data of family size from national statistics and estimated the related influences on indoor heat gains and hot water needs. Su et al. (2019b) estimated the variations in number, usage intensity, and usage time of household devices until 2050 by referring to a forward-looking forecast report and then calculated the temporal energy consumption. (2) Some scholars have addressed the dynamic occupants and behaviors by using simulation tools. Thomas et al. (2016) used EnergyPlus and a system dynamic model to simulate the dynamic electricity and natural gas demands. Su et al. (2017) suggested a simulation of future operational energy levels by forecasting time-varying occupancy profiles.

Existing research regarding this dynamic variable is still insufficient. The types of occupants and behaviors are various, and their potential changes are complex. For example, even by

Table 1 Information of selected DLCA-B studies

Authors (year)	Assessment boundary					Dynamic parameters	Time step	Evaluation object	Location	Dynamic impact category	Pre-/post-assessment
	P	C	O	M	E						
Brattebø et al. (2009)	X	√	√	√	X	Stocks, inflows, outflows, policy, etc.	Annual	BS	Norway	6 categories including abiotic depletion, acidification, etc.	Pre-assessment+ Post-assessment
Caldas et al. (2019)	√	√	√	√	√	GHG emissions, instantaneous radiative forcing, etc.	Annual	Bamboo bio-concrete	Brazil	Global warming	/
Collinge et al. (2011)	X	X	√(15 months)	X	X	Energy and water consumption, CO_2 emission, VOC emission, etc.	Monthly	PB	USA	X (Consumptions and emissions)	Post-assessment
Collinge et al. (2013a)	X	X	√(2 months)	X	X	Occupancy, emissions, temperature, humidity, lighting energy use, etc.	Daily	PB	USA	Respiratory effect, cancer toxicity, and noncancer toxicity	Post-assessment
Collinge et al. (2013b)	X	√	√	√	X	Energy consumption, fuel mix, emission intensity of electricity, characterization factors, etc.	Monthly	PB	USA	10 categories including global warming, human health cancer, etc.	Pre-assessment+ Post-assessment
Collinge et al. (2014)	X	X	√(1 year)	X	X	Temperature, humidity, pollutant emissions, energy consumption, etc.	Monthly	PB	USA	10 categories including global warming, human health cancer, etc.	Post-assessment
Collinge et al. (2018)	X	X	√(3 years)	X	X	Energy consumption, energy mix, emission intensity of electricity, etc.	Monthly	PB	USA	5 categories including eutrophication, respiratory effects, etc.	Post-assessment
Fouquet et al. (2015)	X	X	√	√	X	Energy mix, refurbished material innovation, GHG emissions, instantaneous radiative forcing, etc.	Annual	RB	France	Global warming	Pre-assessment
Frijia et al. (2012)	X	X	√	X	X	HVAC efficacy change	Annual	RB	USA	X (Energy consumption)	Pre-assessment
Gimeno-Frontera et al. (2018)	X	X	√	X	X	Electricity mix, energy consumption, and refrigerant type	Annual	PB	Spain	X (Energy consumption, water consumption and carbon footprint)	Pre-assessment
Hondo (2006)	X	√	√	√	√	Total floor area, demand-supply balance of goods, stability of employment, etc.	Annual	BS	Japan	X (CO_2 emission)	Pre-assessment
Horup et al. (2019)	√	√	√	√	√	Energy grid composition	Annual	Roof windows	Denmark	Global warming	Pre-assessment
Hu (2018)	X	√	√	√	X	Materials and energy consumption, energy mix, emissions intensity of unit energy, and users' value choices	Annual	PB	USA	Global warming, acidification, human health, and ozone depletion	Pre-assessment+ Post-assessment
Ikaga et al. (2002)	X	√	√	X	X	CO_2 emission intensity of unit electricity, energy consumption, population, etc.	Annual	BS	Japan	X (CO_2 emission)	Pre-assessment
Kang et al. (2019)	√	√	X	√	X	Acceptance performance, deterioration, intervention rate, etc.	Annual	RB	Korea	X (Carbon emission)	Pre-assessment
Karl et al. (2019)	X	X	√	X	X	Energy mix	Hourly	PB	Denmark	More than a dozen categories including eutrophication, acidification, ozone depletion, etc.	Post-assessment
Kendall (2012)	√	√	√	√	√	Radiative forcing	Annual	PB	USA	Global warming	Pre-assessment
Lausselet et al. (2019)	√	√	√	X	X	CO_2 emission of unit energy, vehicle type, travel length, etc.	Annual	BS	Norway	X (GHG emissions)	Pre-assessment
Li et al. (2019)	√	√	√	√	√	GDP, population, and residential stock	Annual	BS	China	X (energy consumption)	Pre-assessment
Menconi and Grohmann (2014)	X	X	√ (1 year)	X	X	Outdoor climate, occupants, etc.	Hourly	A sheepfold	Italy	X (energy consumption)	Post-assessment
Mequignon et al. (2013)	X	√	√	√	√	Lifespans of materials and GHG emissions	Annual	External walls	France	X (GHG emissions)	Pre-assessment
Moslehi and Reddy (2019)	X	X	√ (1 year)	X	X	Energy supply	Hourly	BS	USA	Human health and environmental impacts	Post-assessment
Müller and Wömer (2019)	X	X	√ (1 year)	X	X	Energy mix and energy consumptions	15 min	RB	Germany	X (energy consumption and GHG emissions)	Post-assessment
Negishi et al. (2018)	√	√	√	√	√	Occupant behavior, carbon emission, energy mix, and end of life technologies	/	RB	France	Global warming, ecotoxicity and human toxicity	Pre-assessment/ post-assessment
Negishi et al. (2019)	√	√	√	√	√		Annual	RB	France	Global warming	Pre-assessment

Table 1 (continued)

Authors (year)	Assessment boundary					Dynamic parameters	Time step	Evaluation object	Location	Dynamic impact category	Pre-/post-assessment
	P	C	O	M	E						
						Degradation of materials and energy system functions, technological progress, family size, and energy mix					
Österbring et al. (2019)	√	√	√	√	√	Technical and economical driving forces, investment capacity, etc.	Annual	BS	Sweden	12 categories including climate change, acidification, ecotoxicity, etc.	Post-assessment
Peñaloza et al. (2016)	√	√	√	√	√	GHG emissions and instantaneous radiative forcing	Annual	/	Sweden	Global warming	Pre-assessment
Pittau et al. (2018)	√	√	√	√	√	GHG emissions, carbon sequestration, instantaneous radiative forcing, etc.	Annual	Exterior walls	Switzerland	Global warming	Pre-assessment
Pittau et al. (2019)	√	√	√	√	√	GHG emissions, carbon sequestration, instantaneous radiative forcing, etc.	Annual	BS	Europe	Global warming	Pre-assessment
Roux and Peuportier (2013)	X	X	√	X	X	Energy consumption and energy mix	Hourly	RB	France	12 categories including global warming, acidification, eutrophication, etc.	Post-assessment
Roux et al. (2016a)	X	X	√	X	X	Temperature change and energy mix	Hourly	RB	France	12 categories including acidification, water, waste, etc.	Pre-assessment
Roux et al. (2016b)	X	X	√(1 year)	X	X	Electricity consumption and electricity mix	Hourly	RB	France	12 categories including energy demand, water consumption, abiotic depletion, etc.	Post-assessment
Roux et al. (2017)	X	X	√	X	X	Electricity consumption and electricity mix	Hourly	RB	France	X (energy consumptions)	Post-assessment
Russell-Smith and Lepech (2011)	X	√	√	X	X	Energy and materials consumption	Annual	/	USA	Global warming, energy consumption, acidification, eutrophication, and carcinogens	Pre-assessment
Sandberg and Brattebø (2012)	X	X	√	X	X	Energy consumption and energy mix	Annual	BS	Norway	X (Energy consumption and GHG emissions)	Pre-assessment
Säynäjoki et al. (2012)	√	√	√	√	X	Carbon emissions of unit energy	Annual	RB	Finland	X (GHG emissions)	Pre-assessment
Sohn et al. (2017a)	X	X	√	X	X	Energy mix	Annual	Insulation components	Denmark	Global warming	Pre-assessment
Sohn et al. (2017b)	X	X	√	X	X	Energy mix	Annual	Insulation components	Denmark	16 categories including acidification, climate change, land use, mineral depletion, etc.	Pre-assessment
Su et al. (2017)	X	X	√	√	X	Technology, occupancy behaviors, characterization factors, and weighting	/	RB	China	More than a dozen categories including acidification, water depletion, etc.	Pre-assessment
Su et al. (2019b)	√	√	√	√	√	Material and energy consumption, basic inventory datasets, characterization factors, and temporal environmental policy	Annual	RB	China	9 categories including global warming, acidification, iron ore resource, etc.	Pre-assessment
Su et al. (2019c)	√	√	√	√	√	Temporal environmental policy	Annual	RB	China	9 categories including global warming, acidification, primary energy depletion, etc.	Pre-assessment
Thomas et al. (2016)	√	√	√	√	√	Occupant and behaviors, and material degradation	Annual	PB	USA	X (energy consumption)	Pre-assessment
Toller et al. (2013)	X	X	√	X	X	Energy consumption, emissions and wastes	Annual	BS	Sweden	X (energy consumption, emissions and wastes)	Post-assessment
Vuarnoz and Jusselme (2018)	X	X	√	X	X	Flows of energy types and carbon conversion factor	Hourly	RB and PB	Switzerland	X (GHG emissions)	Post-assessment
Wang et al. (2018)	√	√	√	X	√	Discount rate	Annual	RB	China	16 categories including ozone depletion, climate change, toxicity, metal depletion etc.	Post-assessment
Williams et al. (2012)	√	√	√	√	X	Climate change, energy demand, and GHG emissions	Annual	PB	UK	X (GHG emissions)	Pre-assessment

Table 1 (continued)

Authors (year)	Assessment boundary					Dynamic parameters	Time step	Evaluation object	Location	Dynamic impact category	Pre-/post-assessment
	P	C	O	M	E						
Zhang (2017)	√	√	√	X	√	Unit pollution damage cost and discount rate	Annual	RB	China	X (CO_2 emission)	Pre-assessment
Zhang and Wang (2017)	√	√	√	√	√	Efficient electricity generation and weighted delayed emissions	Annual	RB	China	X (Carbon emissions)	Pre-assessment

Note: / unknown, √ included, X excluded. *P* production activities, *C* construction activities, *O* operation activities, *M* maintenance and repair activities, *E* end of life activities. *RB* residential building, *PB* public building, *BS* building stock

simply examining the air conditioner usage behaviors, 25 behavior patterns were produced in a study (Su et al. 2019a). The current DLCA-B studies have only addressed a few types. For future studies, descriptions of potential variations in the types of occupants and behaviors and the quantification of their influences on consumption are vital undertakings.

Energy evolution

Energy is an essential expenditure for buildings owing to the large amount of consumption associated with them. It is also a major contributor to environmental damage because it discharges considerable GHGs, especially in the form of CO_2. Energy evolution over time appreciably affects the environmental performance of buildings, and it has been recognized as a significant dynamic variable. Energy evolution primarily originates from two aspects: energy mix improvement and production efficiency promotion. They are introduced in the following two paragraphs.

Renewable energy will make up an increasing share of future grid mixes. Energy mix improvement is an upcoming trend. It will change the composition of a unit energy and affect the input and output flows. The energy mix improvement has been addressed by various approaches, and the following are three typical approaches in current DLCA-B studies. (1) Some studies have quantified future energy mix by varying the mix composition, as shown in the calculation formula (1). The impacts of one unit energy grid are an aggregation of the impacts of various energy sources according to their shares. Roux et al. (2016b) estimated temporal energy mix on an hourly basis and a yearly basis with data from statistics. Negishi et al. (2019) conducted an inventory analysis for future energy mix in two scenarios. Su et al. (2019b) and Roux et al. (2017) calculated the basic inventory datasets of one unit energy grid with inventory databases. (2) Some scholars have modeled future energy mix by adopting scenario analyses and prediction tools. Gimeno-Frontera et al. (2018) set scenarios according to EU policy planning to describe prospective changes in electricity generation mix. Horup et al. (2019) adopted five different forecasts of future energy mix in Denmark. Roux et al. (2016a) used a high temporal resolution model to simulate the time-dependent electricity system in France by 2050. (3) Some studies have directly acquired time-dependent energy generation mix data from historical statistics (Collinge et al. 2018; Vuarnoz and Jusselme 2018) and from future development reports (Fouquet et al. 2015).

$$I(t) = \frac{P_{\mathrm{i}}(t)}{\sum_{\mathrm{i}} P_{\mathrm{i}}(t)} \times I_{\mathrm{i}} \tag{1}$$

where $I(t)$ is the vector of impacts of one unit of energy grid at time t; $P_{\mathrm{i}}(t)$ is the production amount of energy type i at time t;

I_i is the vector of impacts of one unit of energy type *i*; and *i* represents different energy types.

In contrast, few scholars have examined the promotion of energy production efficiency and related influences. Energy production efficiency promotion saves raw materials and produces less emissions. Ikaga et al. (2002) set three scenarios to quantify the potential changes in CO_2 emissions from unit electricity production over time. Collinge et al. (2013b) and Hu (2018) adopted time-varying air pollutant emission intensities of different fuel types in assessments, and the data were from the US Environmental Protection Agency.

Degradation of materials and devices

Due to the influence of external conditions and excessive usage, the technical performance of construction materials and devices degrades over time (Thomas et al. 2016). The degradation of the insulation materials used for walls, roofs, and floors leads to considerable changes in energy consumption (Choi et al. 2018; Stazi et al. 2014). These processes and changes occur slowly and slightly. However, given the long lifespan of buildings, they are worthy of attention.

Until now, limited studies have considered this dynamic variable. Negishi et al. (2018) discussed it in theory. They later involved the heat transfer performance degradation of three insulation materials and the energy efficiency reduction of electric convectors and heat pumps in an application study (Negishi et al. 2019). Related dynamic data were primarily derived from other studies. Thomas et al. (2016) generated three material performance curves and then assessed the related influences on operational energy demand. However, the dynamic data in these studies were not combined with the specifics of the evaluated buildings and only reflected the average levels. Future studies could make improvements on this front.

Carbon absorption

Some materials used in buildings have the capacity to absorb carbon, which influences carbon flows and EI results. For example, bio-based construction products discharge emissions through biomass transformation and uptake carbon through plants. Lime-based materials can bind CO_2 from the atmosphere through the carbonation process. The carbon absorption process is very slow and may require several decades to occur.

Very few DLCA-B studies have attempted to integrate this variable into assessment. Only Pittau et al. (2018) considered carbon absorption in an application, and the related data were obtained from other research studies. Many studies have specifically focused on quantifying the carbon absorption of biogenic materials (Levasseur et al. 2013; Peñaloza et al. 2016) and lime-based materials (Despotou et al. 2016; Pavlík et al. 2012). These studies could provide a research foundation and data for considering dynamic carbon absorption in future DLCA-B studies.

Expected service lives of components and devices

Building structures and products have long life cycles, nearly 40–100 years. However, the involved components and devices typically cannot survive that long according to the reliability standards in many countries (British Standards Institute 2002; International Code Council 2018; MOHURD and GAQSIQ 2018). An ESL of 30 years is often used for floors, roofs, and drain pipes and 10 years for painting and air conditioners (Wang 2011; Zhang and Wang 2017). The technical performances of these components and devices will diminish over time and, ultimately, be useless at the end of their lives, when they have to be replaced or refurbished. Related manufacturing, transport, and installation activities will bring EIs. Some traditional LCA studies of buildings have assumed that these components and devices have the identical life cycles as the structures and choose to neglect related activities and EIs (Li et al. 2019; Wang et al. 2018). However, DLCA-B research involves a time dimension, and this variable should be considered.

Current DLCA-B studies have estimated the replacement frequencies of components and devices mostly according to their ESLs. Subsequently, the corresponding EIs due to these periodic replacement and refurbishment activities could be assessed. The data of the ESLs of components in these studies came from standards (Su et al. 2019b) and literature (Zhang and Wang 2017). However, these data were empirically designed values and may be different from the actual situations. It is more accurate to identify ESL data according to the local climate and usual practices. Recently, intelligent maintenance and management systems for components and devices have developed rapidly. This may uncover new research ideas and opportunities to address this dynamic variable.

Temperature change

Temperature changes over time influence indoor heating/cooling demands and subsequently affect the operational energy consumption of buildings (Wei et al. 2014). Until now, only two DLCA-B studies have tried to assess the influence of temporal climate change on the EIs of buildings. Williams et al. (2012) used a weather generator to obtain temperature data on an hourly basis and then modeled the annual heating and cooling energy demands. Roux et al. (2016a) developed four temperature scenarios up to 2100 by using a meteorological data prediction tool and assessed the varying EIs of buildings.

Although the influence of climate change on operational consumption has been recognized, very few DLCA-B studies have considered this dynamic variable. The primary reason may be the knowledge gap. Discovering a method to scientifically forecast climate change is a persistent concern in the environmental research field.

Technological evolution

Maintenance, repair, and EOL activities typically occur decades after the original construction activities. Thus, technological evolution over time could affect these activities and the corresponding EIs. Current DLCA-B studies have illuminated the role of technological evolution from two perspectives: production technique evolution and on-site construction technique evolution. The following two paragraphs introduce their research progress.

With the evolution in the production technique of materials and devices, greener components and devices with longer lifetimes may be used in maintenance and repair activities (Negishi et al. 2018). The current DLCA-B studies only focused on this evolution for a few materials and devices. The involved dynamic data were mainly from literature review and expert opinions. Fouquet et al. (2015) considered the GHG emission reductions in cement and expanded polystyrene. Negishi et al. (2019) roughly assumed a 10% energy reduction each decade for material production. Frijia et al. (2012) proposed a few improvement scenarios for efficiency changes in HVAC systems. In fact, thousands of material types are involved in a building. Determination of the potential influences of technological evolution on each material and component is impossible. Therefore, focusing on the technological evolution of some major components and devices is a workable solution at present.

On-site construction techniques will improve and become more efficient over time. For repair activities, energy consumption and material loss due to the installation of a component may be different from those during the original construction phase. For EOL activities, related input-output flows may significantly vary from the current levels. However, predicting these improvements and quantifying the related influences on assessment results is complex. Only theoretical analyses have been performed in existing DLCA-B studies (Su et al. 2019b; Wang et al. 2018).

Waste recycling rates

At the end of the life of a building, the waste must be disposed of. Recycling is a typical treatment measure. Given that the current recycling rates of wastes in many countries are not satisfactory, the potential improvement of recycling levels has attracted some attention. Some scholars have adopted higher recycling rates in their DLCA-B studies by using assumptions, adopting scenario analyses (Su et al. 2019b), and referring to planning documents (Negishi et al. 2019). The quality of these dynamic data still has room for improvement.

Summary

Eight building-related dynamic variables were analyzed, and they can be classified into three levels according to their attributes: the external level (including energy evolution, temperature change, technological evolution, and waste recycling rates), the building system level (including degradation of materials and devices, carbon absorption, and ESLs of components and devices), and the end-user level (occupants and behaviors). The dynamic variables at these three levels had different research progress and were addressed using different approaches, as summarized in Table 2.

- Research on the dynamic variables at the external level relied heavily on the maturity of the research in environmental and industrial areas. Literature review and scenario analysis were frequently adopted to quantify the possible variations of these dynamic variables. Some scholars used a weather generator (Williams et al. 2012) and a prediction model (Roux et al. 2016a) to collect the temporal data of temperature. The related dynamic data were mainly from historical records, reports, and assumptions.
- The quantification of the dynamic variables at the building system level requires specialized knowledge of building materials and devices. The current studies primarily utilized empirical data and other research achievements, failing to conduct specific dynamic assessments according to the unique characteristics and actual situation of the assessed building.
- As far as the dynamic variable at the end-user level, prediction analysis (Su et al. 2019b) and simulation tools (Thomas et al. 2016) were adopted to address it. During recent decades, many intelligent tools and software have been developed to introduce occupants and behaviors into energy simulations. Scientifically embedding temporal variations into these tools may be a potential direction.

These dynamic variables play roles in various life cycle phases of a building, as shown in Fig. 2. The life cycle of a building can be divided into a pre-use phase (extraction and manufacture of raw materials, transport, construction, and installation), a use phase (operation, repair, and maintenance), and an EOL phase (demolition and disposal). The use phase spans the longest duration, and most dynamic variables influence activities during this phase. The input-output flows in the EOL phase would be affected by technological evolution and waste recycling rates. Barely any studies have discussed the dynamic variables during the pre-use phase. Some scholars believe that the pre-use phase is usually very short, only a few years in length, and the related temporal variations might be small (Su et al. 2019b). Neglecting potential variations

Table 2 The addressing approaches and data sources of building-related dynamic variables

Classification	Dynamic variables	Addressing approaches	Data sources	Representative studies
External level	Energy evolution, temperature change, technological evolution, and waste recycling rates	Literature review, scenario analysis, prediction, etc.	Historical records, reports, assumptions, etc.	Collinge et al. (2018); Fouquet et al. (2015); Frijia et al. (2012); Roux et al. (2016a); Sohn et al. (2017b); Williams et al. (2012)
Building system level	Degradation of materials and devices, carbon absorption, and ESLs of components and devices	Literature reviews	Other studies	Mequignon et al. (2013); Pittau et al. (2018); Thomas et al. (2016)
End-user level	Occupants and behaviors	Prediction analysis and simulation	Statistical materials, reports, other studies, etc.	Negishi et al. (2019); Su et al. (2019b); Thomas et al. (2016)

during the pre-use phase and using static data were common in current DLCA-B studies.

The above analysis clearly illustrates that DLCA is a comprehensive multidisciplinary research topic, involving environmental science, engineering, and sociology. Conducting a DLCA is complex. Its development and application require more cooperation among scholars from different backgrounds.

Other dynamic variables

This section analyzes three typical dynamic variables that are not related to buildings: characterization factor, weighting factor, and significance of impacts at different times.

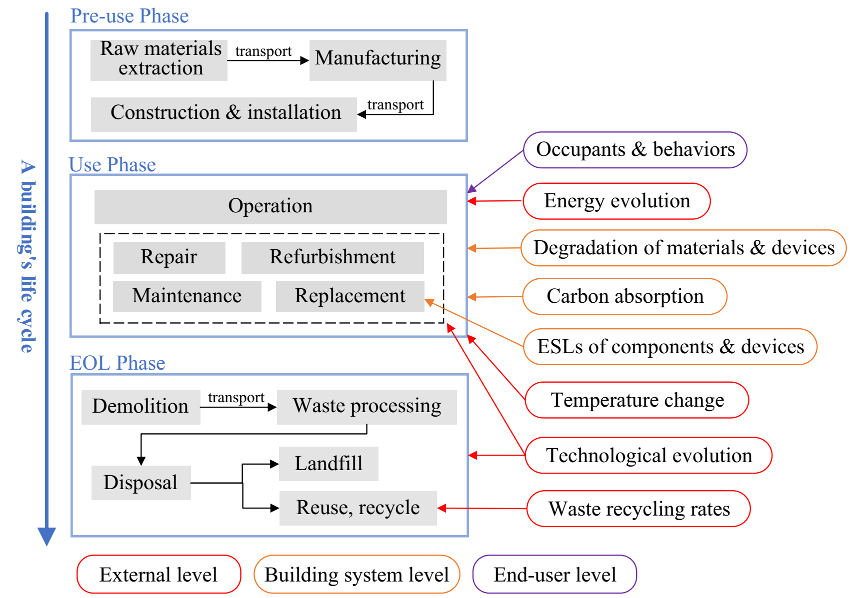
Characterization factor

Dynamic characterization studies considered time-dependent processes such as mass transfer and chemical reaction and acknowledged the differences in consequence due to emissions released at different times. Levasseur et al. (2010) proposed a dynamic characterization model for global warming impact. They calculated instantaneous radiative forcing caused by each pulse carbon emission according to when it took place in time. The dynamic characterization formulas and values were directly adopted by many DLCA-B studies (Caldas et al. 2019; Fouquet et al. 2015; Pittau et al. 2019). In addition, Ericsson et al. (2013) used the temperature change indicator to conduct temporal characterization, and related achievements were adopted by Negishi et al. (2019) to measure the increase in temperature due to a building's activities. Until now, dynamic characterizations for other impact categories have not been well addressed in DLCA-B studies.

Weighting factor

Weighted results could better support comparison and decision-making, and the time-dependence of weighting factors has drawn some attention. Some scholars (Su et al. 2017; Wu et al. 2005) pointed out that the environmental priorities of different impact categories may change with external conditions. To solve this dynamic issue, Su et al. (2019c) calculated short-term, medium-term, and long-term weighting factors using targets from governmental environmental policy and planning reports. Zhang (2017) thought that people's willingness of paying a given amount of money to avoid global warming would vary over time and established time-dependent data for the unit pollution damage cost of carbon emissions. The used dynamic cost data were obtained from reports produced by the European Investment Bank.

Fig. 2 Dynamic variables and their influenced life cycle phases



Significance of impacts at different times

Some scholars have been concerned with the welfare of future generations and pointed out that EIs that were performed now and in the future needed to be treated differently (Bakas et al. 2015). Some DLCA-B studies have considered this temporal issue. For example, Zhang (2017) proposed discounting to convert impacts that happened at different time points to a common basis. A scenario analysis was conducted with three discount rates (4%, 6%, and 8%) in a residential building application. Hu (2018) emphasized the influences of different users' value choices on assessment results and compared the EIs of an elementary school with discount rates of 5%, 3%, and 0%. Wang et al. (2018) thought that environmental degradation should be considered, and they used four discount rates to measure the time values of EIs.

Summary

Fewer DLCA-B studies have been concerned with the above three dynamic variables. Their values are not specific for the assessed building. Current DLCA-B studies usually directly adopted secondary data from other studies. Literature review and scenario analysis were the major approaches used in these studies (as summarized in Table 3).

In total, 11 dynamic variables were summarized. Among them, energy evolution and characterization factor have received most attention. More than 50% of the selected DLCA-B papers considered energy evolution, and 5 studies even only involved this dynamic variable in their assessments (Gimeno-Frontera et al. 2018; Horup et al. 2019; Karl et al. 2019; Sohn et al. 2017a, b). Nearly 20% DLCA-B studies adopted dynamic characterization factor values. Many of the selected 48 studies involved more than one dynamic variable. Energy evolution and characterization factor were often considered together in a dynamic study (Collinge et al. 2013b; Fouquet et al. 2015; Hu 2018). Besides, occupants and behaviors and degradation of materials and devices were also involved simultaneously (Negishi et al. 2018, 2019; Thomas et al. 2016).

DLCA models for buildings

Some research groups have proposed specialized DLCA models for buildings to provide assessment methodology. The followings are three typical ones: the dynamic matrix model, the data transformation–based model, and the static model + dynamic variables. The frameworks and detailed information of these three dynamic models are provided in Figures S1–S3.

Dynamic matrix model

Collinge et al. pioneered DLCA-B research early and used dynamic matrices to perform the assessment process and proposed a dynamic model (Collinge et al. 2013b). The calculation formula is shown below. C_t focused on temporal characterization factors; B_t captured varying environmental interventions for each process; A_t considered the upstream process changes, which were independent of building management decisions, such as the energy mix; and f_t represented the varying required materials and energy amounts from various activities. When conducting a dynamic assessment, the influences of dynamic variables on these four matrices were quantified. Temporal matrices were developed, which may be

Table 3. Parameters and addressing approaches of three dynamic variables

Dynamic variable	Parameter	Addressing approaches
Characterization factor	Instantaneous radiative forcing	Literature review and calculation formulas
	Surface temperature change	Literature review
Weighting factor	Temporal environmental policy	Distance to target approach and calculation formulas
	Unit pollution damage cost	Literature review and calculation formulas
Significance of impacts at different times	Discount rate	Scenario analysis and literature review

mathematical functions of time or a time series. Finally, dynamic EIs were assessed using these dynamic matrices.

$$h_t = \sum_{t_0}^{t_e} C_t \cdot B_t \cdot A_t^{-1} \cdot f_t \tag{2}$$

where h_t is a temporally varying EIs vector, C_t is an environmental system dynamic matrix, B_t is an inventory dynamic matrix, A_t is a supply chain dynamic matrix, and f_t is dynamic building operation vector.

This dynamic model was adopted to quantify human health impacts (Collinge et al. 2013a), assess productivity performance in office buildings (Collinge et al. 2014), and compare the dynamic impacts of a conventional green building and a net zero energy building (Collinge et al. 2018). In addition to Collinge's research group, some other scholars also used dynamic matrices to present assessment. Hu (2018) replaced the characterization matrix with a new "M" matrix of users' choice values. The "M" matrix represented a dynamic weighting system, and three archetypes (hierarchist, egalitarian, and individualist) with different environment priorities and discount rates were analyzed. Fouquet et al. (2015) and Pittau et al. (2018) simplified the above dynamic model and used GHG emission vector and environmental system dynamic matrix to assess dynamic global warming impacts.

Data transformation–based model

Su et al. analyzed the transformation of calculation data in EI assessment and proposed four types of dynamic assessment elements. The dynamic model was termed "data transformation–based model" in this study. They developed a dynamic framework in 2017 (Su et al. 2017), discussed some prospective approaches, and conducted an application study (Su et al. 2019b). In this model, dynamic variables affected the values of four types of dynamic assessment elements. The final dynamic impact results were calculated by following the data transformation pathway. Here are the assessment steps. First, building material and energy consumption data during the whole life cycle were collected annually. Then, dynamic consumption data were transformed into dynamic inventory results with time-dependent energy mix considered. Later, dynamic characterization factors that allowed for the timing of pollutants were adopted to achieve dynamic impact category indicators. Finally, dynamic weighting factors quantified the severities of impacts at different times and outputted annual impacts.

Static model + dynamic variables

Negishi et al. introduced dynamic variables individually based on a static LCA model. It is termed "static model + dynamic variables" in this study. They proposed a dynamic framework and discussed some dynamic characteristics in 2018 (Negishi et al. 2018) and later quantified the variations of some dynamic variables and conducted an application (Negishi et al. 2019). The developed dynamic model included five steps. First, building data were collected and some dynamic aspects were discussed. In the second step, a static model of the life cycle system was developed. Then, the involved dynamic variables were analyzed and modeled using various scenarios. The last two steps conducted a dynamic inventory analysis and a dynamic characterization to achieve temporal EIs. In this model, the static LCA system was developed as a base, and various dynamic variables were incorporated into the static system to perform the dynamic assessment.

Comparison

The above three typical DLCA models have specific advantages and limitations, and they are compared in Table 4.

- The dynamic matrix model was concise and clear. However, it missed the dynamic characteristics and specifics of buildings. In fact, it was generally applicable to all products. Besides, temporal information was merely expressed as "t" in this model without a detailed analysis and further discussion. It remained unclear how to completely identify dynamic variables and scientifically quantify them. This was a significant obstacle for application.
- The data transformation–based model built a bridge between the temporal information and traditional assessment procedures, making it easy to incorporate dynamic

Table 4 A comparison of three typical DLCA models

Model	Main content	Advantage	Limitation
Dynamic matrix model	Four matrices: environmental system dynamic matrix, inventory dynamic matrix, supply chain dynamic matrix, and dynamic building operation vector	It was concise and clear	The involved temporal information needed further analysis
Data transformation–based model	Four types of dynamic assessment elements: dynamic consumption, dynamic basic inventory datasets, dynamic characterization factors, and dynamic weighting factors	It built a bridge between the temporal information and traditional assessment procedures	It did not provide deep discussion regarding the temporal attributes of some dynamic variables
Static model + dynamic variables	Five steps: data calculation and collection, static model of the life cycle system, temporality of the building life cycle system, dynamic model of the life cycle system, and dynamic impact assessment calculation	It was easy and clear to understand	It lacked a complete and systematic expression regarding the involved dynamic variables

variables with the existing LCA framework. Unfortunately, it did not provide deep discussion regarding the temporal attributes of some dynamic variables.

- The research idea in the "static model + dynamic variables" model was easy and clear to understand. However, it lacked a complete and systematic expression regarding the involved dynamic variables.

Existing problems and future directions

This study systematically analyzed the DLCA-B literature, synthesized the involved dynamic variables, and compared some dynamic assessment models. The following discussion reviews the existing problems and proposes potential research directions (as shown in Fig. 3).

Pre-assessment and post-assessment comparison

Current DLCA-B studies could be pre-assessed using predicted future data and post-assessed using historical data. Nearly 70% of the selected DLCA-B papers belong to the former. These two assessment types have specific advantages and limitations. The post-assessment results are more accurate for the used data consists of actual values. Post-assessments are more meaningful for short-life products in standardized production modes because effective measures and schemes could be proposed on the basis of assessment results. This could serve to improve the next round of manufacturing upgrades. However, building processes are less standardized than industrial processes. Every building is specific and possesses unique characteristics. Thus, the lessons and improvement suggestions from one building may have limited referential values for other buildings. More importantly, the life cycles of buildings are long, up to 40–100 years. The guidance value of results is relatively small for future buildings.

In contrast, pre-assessment results can help identify major EI sources and provide a basis for improving the design and use (Li et al. 2017). Pre-assessment studies have been preferred in the past decade among DLCA-B studies and will continue to be preferred in the future (Collinge et al. 2013b). However, dynamic pre-assessment still faces some problems. First, there is limited knowledge regarding future technologies, and this creates new uncertainties (Collinge et al.

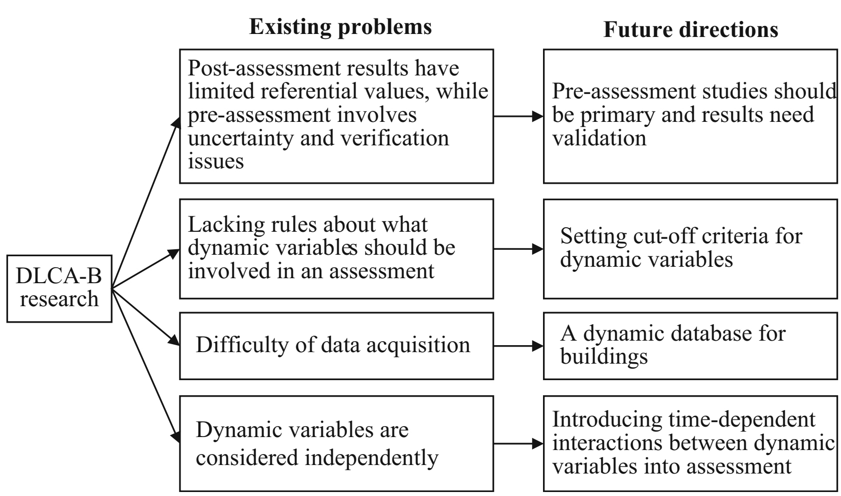


Fig. 3 Existing problems and future research directions of DLCA-B research

2013b; Hu 2018). Second, the workability of a pre-assessment model can be verified using cases and applications, as accomplished in many of the reviewed DLCA-B studies. However, the accuracy and reliability are still unproven, and until now, no studies have performed the necessary analyses. This is a difficult but significant barrier. Future research could try to solve these problems.

The cutoff criteria for dynamic variables

This review summarized 11 dynamic variables, and only a few of them were considered simultaneously in current DLCA-B studies. Neglecting some dynamic variables was taken as a research limitation (Collinge et al. 2018; Roux et al. 2016a). The following questions arise: How does the assessment practitioner decide which dynamic variables should be included in his assessment? How does the practitioner draw fair boundaries for the different building systems being compared? The current DLCA-B studies scarcely discussed or tried to address the above questions. Su et al. (2019b) thought that only the variations that could be predicted and significantly influence the final results should be considered. However, no measure of the significance has been clearly stated.

There is a need to learn from traditional LCA studies and develop cutoff criteria for dynamic variables. In traditional LCA studies, a series of cutoff criteria are established to determine which elementary flows should be included in assessments and to define the maximum level of detail (Raynolds et al. 2000). The ISO 14044 standard (ISO 2006) suggests the use of mass, energy, and environmental significance as cutoff criteria. In dynamic assessments, cutoff criteria should consider both the change degree of dynamic variables and the related environmental significance because a combination of these two aspects influences the final assessment results. (1) A reasonable percentage change would be the baseline for the involvement. If the change in a dynamic variable during the evaluation period is very small and lower than the baseline, it would be reasonable to disregard it to save time and reduce the workload. (2) The environmental significance of the dynamic variable's influence should also be considered. The higher the related environmental significance, the more important the corresponding dynamic variable is, thereby making it more valuable to incorporate this dynamic variable into the assessment. There is a requirement for scientific and reasonable cutoff criteria, and they will play a significant role in future DLCA-B studies.

Dynamic database

Collecting appropriate data to describe the temporal variations of dynamic variables is a difficult job. Most dynamic data are not available directly in existing LCA databases and tools. Limited data availability has been recognized as a significant difficulty in DLCA studies (Collinge et al. 2013b; Su et al. 2019b). The long lifespans and large amounts of materials and products involved in buildings make this issue more pronounced (Breton et al. 2018). As analyzed before, many DLCA-B studies have relied heavily on secondary data from scientific articles, industrial and governmental reports, regulatory documents, and other sources.

A dynamic database for buildings could save the time and effort of practitioners, thereby promoting DLCA-B studies. The prospective values and potential variation ranges of dynamic variables should be included. These dynamic variables are systematically analyzed in the "Dynamic variables" section, which lays a foundation for the development of the dynamic database. Prediction, scenario analysis, virtual reality, and simulation are potentially feasible approaches.

Interactions between dynamic variables

Until now, dynamic variables have been independently introduced into dynamic assessments. However, this is not a realistic simulation. In reality, the external climate change affects the production efficiency of powers, such as wind power (Koletsis et al. 2016), hydropower (Lehner et al. 2005), and nuclear plants (Förster and Lilliestam 2010). The aging rates of building materials vary with changes in the outdoor temperature and humidity.

Involving these interactions would complicate the process of conducting dynamic studies. This review clearly shows that DLCA-B research is at an early stage. Knowledge of some dynamic variables is still immature and incomplete. At this time, research is unable to capture their time-dependent interactions, and shelving these interactions may be a wise choice. Future studies could consider them to enhance and improve this research.

Conclusion

The main aim of this study was to present an overview of DLCA studies in the building field. A total of 48 papers, which were published prior to the end of 2019, were selected and systematically analyzed. The review reveals that there has been a growing interest in DLCA-B research recently. As an emerging research area, DLCA-B is far from mature and requires more in-depth interdisciplinary research.

In this review, 11 dynamic variables were synthesized, including occupants and behaviors, energy evolution, degradation of materials and devices, carbon absorption, ESLs of components and devices, temperature change, technological evolution, waste recycling rates, characterization factor, weighting factor, and significance of impacts at different times. Their research achievements, addressing approaches, data sources, and limitations were analyzed. Three typical dynamic models (i.e., the dynamic matrix model, the data transformation–based model, and the "static model + dynamic variables") and assessment steps were comprehensively explained and analyzed. Their advantages and limitations were compared to suggest potential methodologies. Finally, some existing issues in the DLCA-B research were discussed, and future research directions were proposed.

- Pre-assessment studies should be primary, and the involved uncertainty and verification issues require more attention
- Cutoff criteria for dynamic variables are suggested
- A dynamic database for buildings could provide an important data support
- The interactions between dynamic variables are suggested to be considered

This review comprehensively presented the research status quo of DLCA-B studies, while providing references and research directions for future research. The information contained in this study can help practitioners improve building assessments and promote sustainable development. Unfortunately, some latest research achievements were not analyzed since only the DLCA-B papers published prior to the end of 2019 were included in this review.

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Declarations

Ethics approval and consent to participate Not applicable

Competing interests The authors declare no competing interests.

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