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REVIEW ARTICLE

Hui WANG, Yafei YANG

Decomposition analysis applied to energy and emissions: A literature review

Abstract Decomposition analysis has been widely used to assess the determinants of energy and CO_2 emissions in academic research and policy studies. Both the methodology and application of decomposition analysis have been largely improved in the past decades. After more than 50 years' developments, decomposition studies have become increasingly sophisticated and diversified, and tend to converge internally and integrate with other analytical approaches externally. A good understanding of the literature and state of the art is critical to identify knowledge gaps and formulate future research agenda. To this end, this study presents a literature survey for decomposition analysis applied to energy and emission issues, with a focus on the period of 2016–2021. A review for three individual decomposition techniques is first conducted, followed by a synthesis of emerging trends and features for the decomposition analysis literature as a whole. The findings are expected to direct future research in decomposition analysis.

Keywords index decomposition analysis, structural decomposition analysis, production decomposition analysis, energy, CO_2 emissions

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Hui WANG (✉)
School of Economics and Management, China University of Petroleum, Qingdao 266580, China; Institute for Energy Economics and Policy, China University of Petroleum, Qingdao 266580, China
E-mail: wh@upc.edu.cn

Yafei YANG
School of Economics and Management, China University of Petroleum, Qingdao 266580, China

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1 Introduction

Decomposition analysis is a useful tool in energy and climate policymaking. As an accounting approach, decomposition analysis distributes a change in an aggregate indicator of interest to policymakers to a set of pre-defined factors that have policy relevance. The decomposition results can therefore explain the change in the indicator, which provides a quantitative understanding of the underlying dynamics with managerial implications. Applying the decomposition approach, for example, IEA (2022) examines the effectiveness of energy efficiency improvement on global energy use, IPCC (2022) assesses the technical and socioeconomic drivers of global CO_2 emissions, and Keramidas et al. (2021) evaluates how the COVID-19 and 2 °C target affect energy system and emissions. Such information is usually fundamental to the formulation and assessment of energy and climate policies. As a result, decomposition analysis has been widely used in policy studies by international organizations (Zhong, 2015; World Bank, 2015; UNFCCC, 2021) and governments worldwide (Rørmose, 2010; Wright, 2014; Natural Resources Canada OEE, 2016; Emele et al., 2022; US EIA, 2022).

Due to its widely-recognized practical usefulness, decomposition analysis has flourished in academic research since proposed in the 1970s. As of March 2023, over 10000 decomposition studies are found on Google Scholar. A large body of the literature are devoted to studying the methodological and application issues of decomposition analysis. Since similar to the construction of index numbers in nature, a key theoretical pillar of decomposition analysis relies on the index number theory (Boyd et al., 1988; Hoekstra and van den Bergh, 2003). From a systems science viewpoint, the methodological foundations of decomposition analysis are built from the perspectives of energy, economic and production systems (Ang, 2004; Lenzen, 2016; Wang et al., 2017a). A wide variety of decomposition models are developed to respond to the diverse needs and challenges in policy analysis (Su and Ang, 2012; Wang et al., 2018b; Ang and Goh, 2019). To better perform decomposition, theoretical properties of calculation methods are studied to ensure consistent results across decomposition strategies and no residual exists (Ang, 2015; de Boer and Rodrigues, 2020). With these methodological progresses, the application of decomposition analysis has also been significantly expanded in terms of scope, scale and dimension.

After more than 50 years' developments, decomposition analysis has become increasingly mature with new features ever emerging. At present, three branches of decomposition analysis exist in the literature, i.e., index decomposition analysis (IDA), structural decomposition analysis (SDA) and production decomposition analysis (PDA).[1)] With the same purpose of assessing determinants of indicators, the three techniques differ in modelling, application and thus implications delivered. More recently, decompositions become sophisticated and tend to converge internally and integrate with external approaches. These diversities in decomposition studies create ambiguities and even confusions to researchers and analysts. A good understanding of the literature and particularly recent developments helps to better grasp the state of the art and identify research gaps. To this end, this paper presents a systematic review of the decomposition analysis literature. Given its main application area and to avoid overlapping with previous surveys, this review is confined to decomposition analysis applied to energy and CO_2 emission issues and mainly focuses on the literature for 2016–2021. We first present an overview of the decomposition studies collected, followed by a detailed review for the three decomposition techniques separately. The key features and trends of the entire decomposition analysis literature are then analyzed. The findings are expected to direct future research agenda setting for decomposition analysis.

The rest of this paper is structured as follows. Section 2 briefly introduces the decomposition approach. Section 3 conducts a bibliometric analysis of the decomposition literature. Section 4 identifies key developments for three decomposition techniques separately, and Section 5 presents a synthesis. Section 6 concludes and discusses future research directions.

2 Decomposition analysis approach

Decomposition analysis begins with modelling an aggregate indicator in the form of index numbers, e.g., $V = \sum_i u_{1i}u_{2i} \cdots u_{ni}$, where a change in the aggregate indicator V during a time period can be explained by changes in the pre-defined factors u at sub-aggregate level i. Following this idea and adapting to varying needs of analysis, three decomposition analysis techniques are developed.

Originating from energy balance analysis, IDA aims to track the flow within and reveal the dynamics of energy systems. Generally IDA models an aggregate indicator from three aspects, i.e., the intensity, structure, and overall scale of relevant activities. Taking national energy consumption as an example, the simplest three-factor IDA model is given in Table 1. Accordingly, an energy consumption change is decomposed into the intensity effect that indicates the impacts of energy use technologies, the structure effect arising from shifts in composition of energy end-use activities, and the activity effect that captures the scale of overall energy end-use activities, as shown in Table 1. In this manner, IDA quantifies the determinants of energy and emissions by end-use activities from an energy systems perspective.[2)]

SDA aims to capture the energy and emission consequences of structural changes in both production and demand. To this end, SDA is built upon the input–output (IO) model that portrays economic dependencies between sectors and regions. With the relationship between supply and demand established by the IO model and combined with energy intensity multipliers, a country's energy use can be modelled with production flows that satisfy consumption, as shown in Table 1. An energy use change can therefore be decomposed into the intensity effect that signals energy use technological change, the production structure effect that captures changes in production linkages between sectors/regions, the demand structure effect that reflects shifts in consumption pattern, and the total demand effect that indicates the scale of final demand (see Table 1). As a result, SDA, from an economic systems perspective, examines the structural impacts of production and demand on energy and emissions.

PDA scrutinizes the energy and emission impacts of technological issues in production processes. For this purpose, PDA is built upon the production theory that well characterizes the general production processes. With technical performance measured, a country's energy consumption is modelled focusing on the technological factors underlying energy use in production, as given in Table 1. Consequently, an energy consumption change can be decomposed into the potential energy intensity effect that captures the impacts of non-energy technologies (e.g., production technology and inputs substitution), the technological change effect that indicates energy-use technology innovation, and the efficiency change effect that reflects energy use efficiency impacts, in addition to the activity structure effect and total activity effect as

[1)] The approach is also termed as the "production-theoretical decomposition analysis" to highlight that it is built upon production theory (Zhou and Ang, 2008). Since the approach primarily focuses on the technological issues involved in production systems, a number of studies also term it as "production decomposition analysis", e.g., Tan and Lin (2018) and Zhou and Kuosmanen (2020). We adopt the simplified term in this study.

[2)] Representative variants of decomposition models and commonly used decomposition methods are given in Appendix A in the Supporting Information.

Table 1 Basic decomposition approaches

Decomposition model		Determinants	Decomposition effects	Explanation
IDA	$E=\sum_i \frac{E_i}{X_i}\frac{X_i}{X}X=\sum_i I_i S_i X$ $E^T-E^0=\Delta E_{\mathrm{int}}+\Delta E_{\mathrm{str}}+\Delta E_{\mathrm{act}}$	Energy intensity of sector i (I_i)	Energy intensity (ΔE_{int})	Energy use technology changes
		Share of activity for sector i (S_i)	Activity structure (ΔE_{str})	Shifts in composition of energy end-use activities
		Total activity (X)	Total activity (ΔE_{act})	Changes in scale of overall energy end-use activities
SDA	$E=\sum_{ij} I_i L_{ij}\frac{Y_j}{Y}Y=\sum_{ij} I_i L_{ij} FS_j Y$ $E^T-E^0=\Delta E_{\mathrm{int}}+\Delta E_{\mathrm{pstr}}+\Delta E_{\mathrm{fstr}}+\Delta E_{\mathrm{tfd}}$	Energy intensity of sector i (I_i)	Energy intensity (ΔE_{int})	Energy use technology changes
		Production structure (L_{ij})	Production structure (ΔE_{pstr})	Changes in production linkages between sectors/regions
		Share of final demand for sector j (FS_j)	Demand structure (ΔE_{fstr})	Shifts in consumption pattern
		Total final demand (Y)	Total final demand (ΔE_{tfd})	Changes in scale of final demand
PDA	$E=\sum_i \frac{E_i/D_{i,E}}{X_i}D_{i,E}\frac{X_i}{X}X=\sum_i PEI_i TE_i S_i X$ $E^T-E^0=\Delta E_{\mathrm{pei}}+\Delta E_{\mathrm{tc}}+\Delta E_{\mathrm{ec}}+\Delta E_{\mathrm{str}}+\Delta E_{\mathrm{out}}$	Potential energy intensity of sector i (PEI_i)	Potential energy intensity (ΔE_{pei})	Non-energy technology changes
		Technical inefficiency of sector i (TE_i)	Technological change (ΔE_{tc})	Energy technology innovation
			Efficiency change (ΔE_{ec})	Energy use efficiency changes
		Share of output for sector i (S_i)	Output structure (ΔE_{str})	Shifts in composition of energy end-use activities
		Total output (X)	Total output (ΔE_{out})	Changes in scale of overall energy end-use activities

Notes: E denotes national energy consumption, the superscripts 0 and T denote time period, and the term $D_{i,E}$ is the distance function that measures the gap between a production entity's performance and the best practice frontier.

appeared in IDA (see Table 1). Thus PDA looks into the technological issues in energy use and emissions from a production systems perspective.

3 Literature overview

As aforementioned, we confine the survey to peer-reviewed articles in English published during 2016–2021. The articles surveyed are collected from Web of Science (WoS), which is one of the world's largest academic databases. A total of 1890 studies are found using the keywords "decomposition analysis", "index decomposition", "logarithmic mean Divisia index", "structural decomposition", "input–output", "production-theoretical decomposition", "energy", and "emission". After initial screening and filtering, a sample of 983 articles is obtained, which covers 602 IDA papers, 314 SDA papers, and 67 PDA papers.

Figure 1 shows the top 10 journals for decomposition analysis literature. They account for 63%, 64% and 68% of the collected papers for IDA, SDA and PDA, respectively. This implies the decomposition analysis literature is fairly concentrated. A number of journals are found popular across the three strands, e.g., *Journal of Cleaner Production*, *Environmental Science and Pollution Research*, *Energy Policy*, *Energy Economics*, and *Applied Energy*. A reason is their interdisciplinary nature and large amount of publications. IDA has become matured in energy system analysis, which makes *Energy Efficiency* and *Renewable and Sustainable Energy Reviews* also popular for IDA studies. As SDA is more frequently applied to environmental studies, a significant number of SDA studies appear in environmental science journals, e.g., *Journal of Environmental Management* and *Science of the Total Environment*. Similarly, since PDA is rooted in production technology modelling, journals such as *Technological Forecasting and Social Change* and *European Journal of Operational Research* are important outlets for PDA studies.

Key articles in the decomposition analysis literature are identified using the citation-based method. We calculate the local citation score (LCS) and global citation score (GCS) for each article. The former indicates the citation frequency of a paper within our sample, while the latter shows that of a paper in the entire WoS database. Since it focuses on the local database of decomposition analysis, the LCS conveys a higher reference value and has widely been used to measure the relative importance of articles (Yu and Shi, 2015; Zhou et al., 2018). According to LCS, the most influential articles in our sample are identified for each of the three decomposition branches, which are listed in Appendix B in the Supporting Information.

The top 50 articles with the largest LCS value are visualized in Fig. 2. Of the 50 studies, there are 29 IDA studies, 17 SDA studies, 3 PDA studies and one review article on both IDA and SDA studies. Generally the bulk of these articles concentrates on methodological developments. For instance, Ang et al. (2016) and Su and Ang (2016) introduce decomposition models catering for multiple dimensions, and Su and Ang (2017) and Wang et al. (2017b; 2017c) deal with intensity indicators modelling. From these studies, common interests are also found across the three decomposition techniques, e.g.,

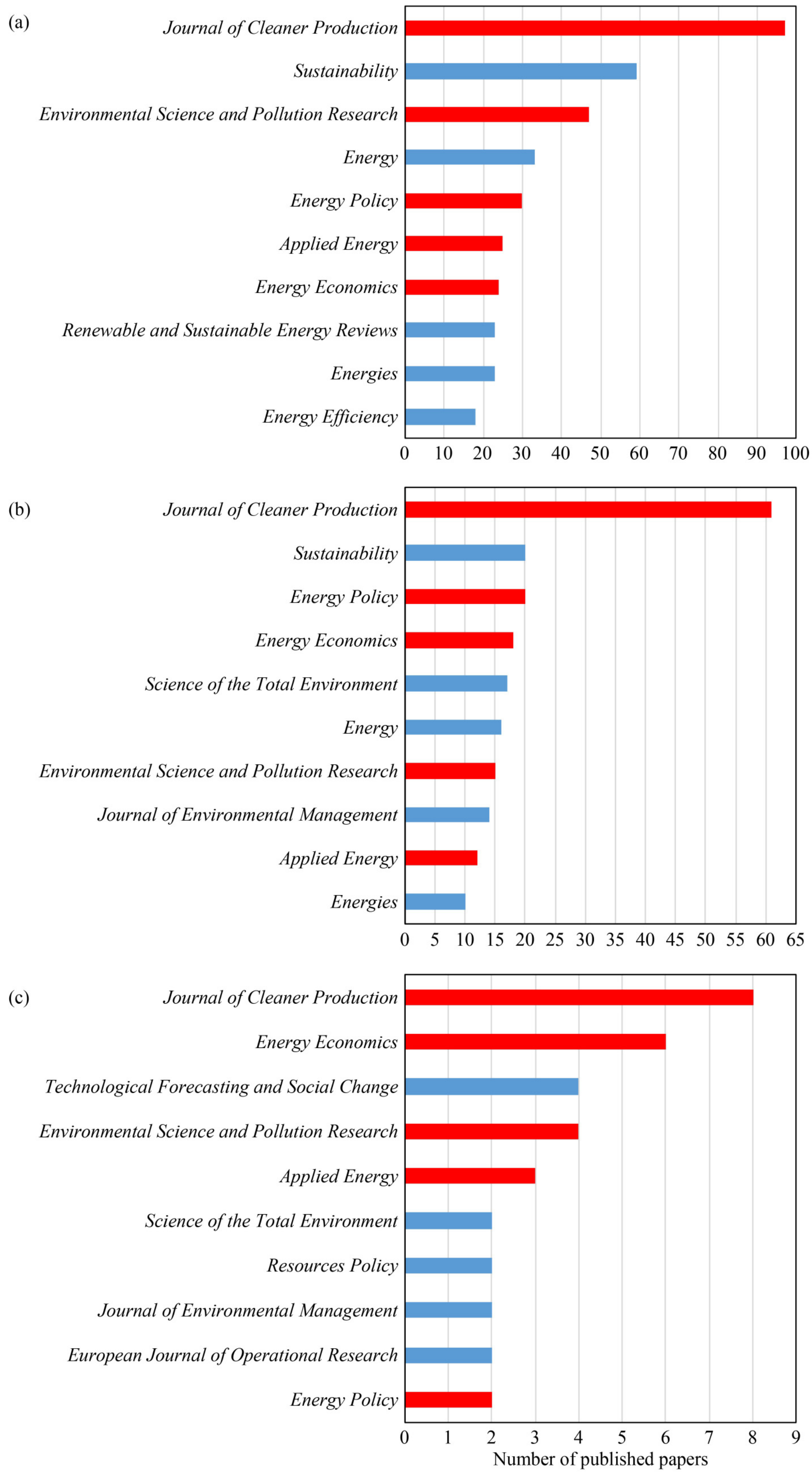

Fig. 1 Distribution of papers among the top 10 journals for (a) IDA, (b) SDA, and (c) PDA (note: red/blue parts refer to the common/unique journals for the three branches of decomposition analysis).

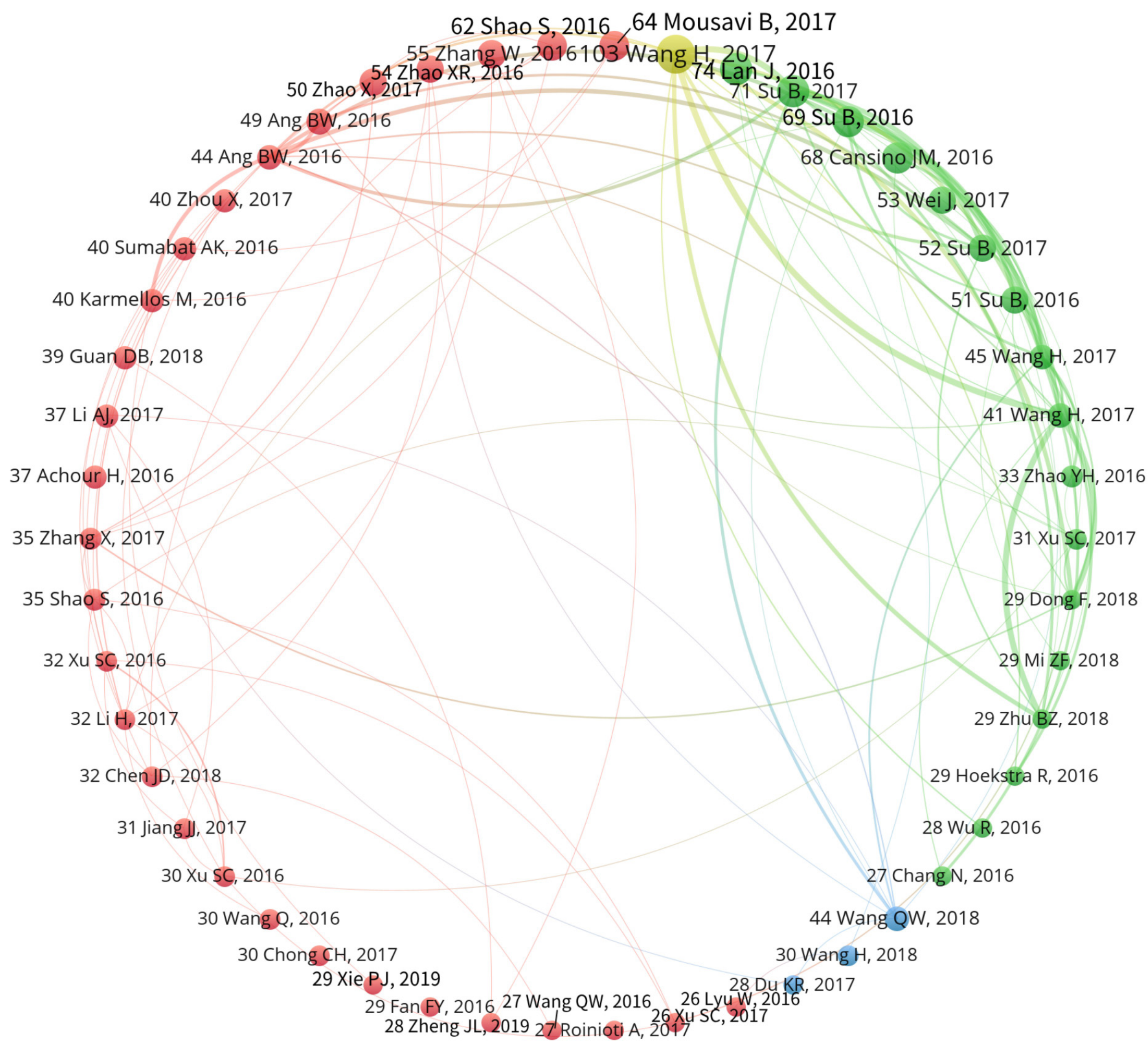

Fig. 2 Citation graph of top 50 decomposition studies (note: the size of circle reflects the magnitude of LCS (the value before author-year in labels); red circles indicate IDA studies, green circles indicate SDA studies, blue circles indicate PDA studies, and yellow circles indicate interdisciplinary studies).

decoupling analysis (Zhao et al., 2016; Roinioti and Koroneos, 2017) and embodied energy/emissions (Su and Thomson, 2016; Lan et al., 2016). These similarities in methodology and application make the literature of three decomposition branches intertwined, as shown in Fig. 2.

4 Recent developments

4.1 IDA

IDA has been extensively studied and applied in energy and emission studies. Due to its simplicity, IDA can be flexibly adapted to various dimensions (e.g., temporal and spatial) and scales (e.g., economies, sectors, firms, and plants) with customizations and extensions in modelling. As IDA is able to isolate the impact of activity intensity on energy use from other factors, it has become a standard tool in monitoring energy efficiency. To operate the decomposition, a number of decomposition methods have emerged, and logarithmic mean Divisia index (LMDI) has been most widely used in the literature given its desirable properties in theoretical foundation and application. As the methodology matures, IDA has penetrated to a broader range of application areas, e.g., air pollutants, material, water, and particularly CO_2 emissions with the rising concern on climate change. These developments of IDA literature up to 2015 are well documented in earlier reviews by Ang and Zhang (2000), Xu and Ang (2013), and Wang et al. (2017a).

Over the period of 2016–2021, the IDA literature generally follows the past trends in terms of key methodological and application features. Figure 3(a) shows that IDA has been widely applied to energy and emissions at both the economy-wide and sectoral levels. CO_2 emission studies take a growing weight, which is four times more

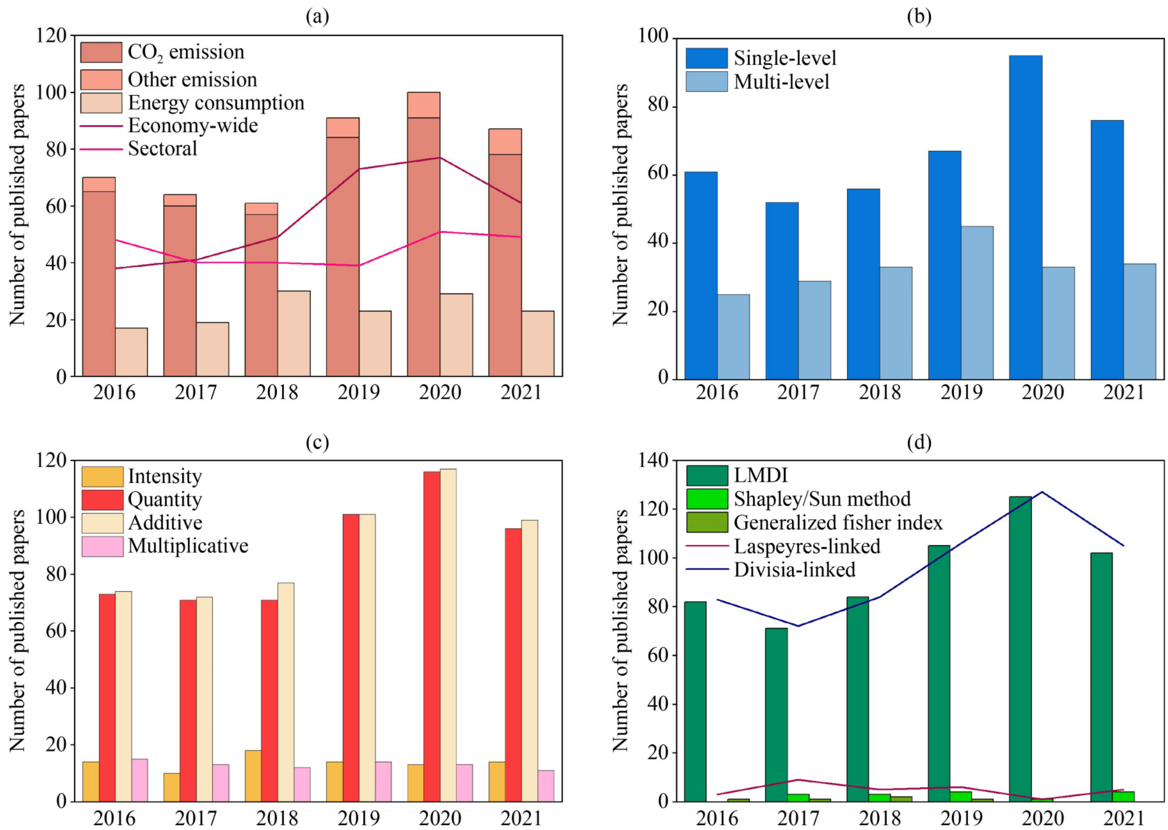

Fig. 3 Methodology and application features of IDA studies, 2016–2021: (a) Total number of IDA studies involving both energy/emissions and at economy-wide/sectoral level; (b) number of studies by single-level and multi-level analysis; (c) number of studies by aggregate indicator and decomposition form; (d) number of studies by decomposition methods.

than energy studies, while a small fraction of IDA studies is devoted to other environmental issues. The multi-level IDA analyses increase steadily[1)], which reflects a need for more detailed results by practitioners and policymakers, as shown in Fig. 3(b). Figure 3(c) indicates that most IDA studies deal with quantity indicators, where additive decomposition is usually adopted to facilitate results interpretation. Figure 3(d) shows a greater popularity of Divisia-linked methods and the dominance of LMDI in decomposition method selection.

Several new developments are found in the IDA literature since 2016. As to the methodology, the decomposition modelling tends to become detailed. In particular, the decomposition identities are usually expanded to detail energy and environmental technologies. Taking the electricity studies as an example, other than the overall intensity and structure of electricity generation as specified in conventional IDA analyses, technological factors, e.g., transmission and distribution (Goh et al., 2018), carbon capture and storage (Ang and Goh, 2019), renewable electricity (Goh and Ang, 2018), and combined heat and power (CHP) (Goh and Ang, 2021; Harmsen and Crijns-Graus, 2021), are increasingly studied. Similar extensions are also found for the building (Zhang et al., 2020a) and transport (Dennehy and Ó Gallachóir, 2018) sectors. This development coincides with the general recognition that technology is central to energy transition and decarbonization (Zhou et al., 2022; Yang et al., 2022; Chen et al., 2022). Based on the advanced modelling and with the more readily available high-resolution data, an increasing number of micro-level IDA applications has been reported. For instance, in addition to the conventional national and provincial analyses, the decomposition of energy use and emissions at the levels of city (Shan et al., 2022), firm (Qian et al., 2021) and end-use devices (Huang, 2020) emerge. Such detailed and micro-level analysis delivers more informative results for policy formulation and evaluation.

Prospective IDA analysis has gained growing attention. Different from retrospective analyses that deal with observed changes in the past, prospective decomposition examines energy/emissions issues in the future, e.g., possible paths and scenarios (Ang and Goh, 2019). Based on the understanding of past energy/emissions patterns and combined with relevant assumptions, IDA modelling from a prospective perspective helps to develop future

1) Multi-level IDA generally refers to the decomposition at two or more levels with hierarchical data, e.g., regional and sectoral air pollutants in Hang et al. (2021). As a counterpart of multi-level decomposition, single-level IDA is only constructed at a particular level based on single-dimension data. See Xu and Ang (2014) for detailed explanations of these two models.

trajectories of energy use (Wang et al., 2018a) and CO_2 emissions (Shahiduzzaman and Layton, 2017). The forecasting is more suitable for short-term analysis as energy/emissions patterns are usually assumed to remain unchanged in such studies. Focusing on a specific energy/emissions path, prospective IDA can quantify the underlying determinants (Mathy et al., 2018; Kone and Buke, 2019). The results present an outlook on the dynamics and driving forces of a particular energy/emissions scenario. To further assess the variation across scenarios, prospective IDA can also be used to capture the sources of differences between scenarios (Yeh et al., 2017; Palmer et al., 2018), which helps to identify barriers and potential opportunities in energy and emissions management. Since uncertainty is inherent in projections and scenarios, several studies attempt to account for the uncertainty issues in prospective IDA studies by combining with Monte Carlo simulation (Zhang et al., 2017; Chen et al., 2021).

IDA has been increasingly used in conjunction with other analytical approaches. As a descriptive technique, IDA is limited in revealing complex interplays between energy/emissions and underlying factors. To overcome this shortcoming, IDA has long been combined with econometric approaches. Recent examples include Cheng et al. (2020) that combines IDA with an econometric regression model to examine the causal effect between fiscal decentralization and CO_2 emissions, and Luo et al. (2021) which couples IDA with the Granger causality analysis. Integrating IDA with optimization models further enables the estimation of energy savings and greenhouse gas reduction potentials (Olanrewaju and Mbohwa, 2017; Fetanat and Shafipour, 2017). Moreover, the coupling of IDA with energy system models, e.g., PRIMES (Fragkos et al., 2017), MESSAGE (Kone and Buke, 2019), TIMES (Yue et al., 2020) and IMAGE (van den Berg et al., 2021), helps to uncover the impact mechanisms behind these "black box" models, which is useful to explore possible trajectories of energy and emissions in mid- and even long-term.

4.2 SDA

To disentangle the complex economic structure and its energy/emissions impacts, SDA has been largely improved and widely applied. Detailed insights regarding the organizational structure of production, e.g., factor inputs and substitution, can be derived by the two-stage decomposition. The demand side can also be scrutinized to explore pattern changes in consumption, investment and export. With the increasingly integrated global/regional production network, SDA has been extended beyond individual economic systems to a multi-region framework. Beyond conventionally temporal analyses, SDA has been adapted to compare energy/emissions disparities across regions and databases. In terms of modelling, other than the usually studied quantity indicators, SDA models with intensity indicators have emerged. Different from IDA, the decomposition method proposed by Dietzenbacher and Los (1998) (hereafter the D&L method) is the convention in SDA, especially for two-stage decomposition analysis. With the methodological progress, SDA has been applied to study energy and emissions issues from different perspectives, e.g., production, consumption, and embodiments in particular supply/demand segments. Key features of SDA literature prior to 2016 are summarized in previous reviews by Su and Ang (2012), Lenzen (2016) and Wang et al. (2017a).

During 2016–2021, the SDA literature largely continues the past trends, as shown in Fig. 4. Figure 4(a) shows that SDA studies are usually confined to the economy-wide level since it is built on the IO table. Arising from the increasing concern on climate change, the emission-related studies have become the majority. Figure 4(b) presents a growing number of two-stage SDA analysis, which reflects a rising interest in assessing the restructuring production network. While the additive decomposition of quantity indicators still dominates the SDA literature, the multiplicative decomposition of intensity indicators has increased, as shown in Fig. 4(c). As to the decomposition method selection, Fig. 4(d) shows that Divisia-linked methods, mainly the LMDI, have become more popular despite the most widely used Laspeyres-linked methods.

Some emerging trends are observed in the SDA studies since 2016. The SDA modelling of technological and structural factors of production has been largely advanced. In the context of energy transition, transformation and generation processes of the energy sectors are investigated in greater details by disaggregating production technologies (Guevara and Rodrigues, 2016; Li et al., 2019), which improves the modelling of technological changes in economic systems. The organizational structure of production networks is studied from a variety of aspects, e.g., goods composition, regional distribution and firm type (Wood et al., 2020; Dietzenbacher et al., 2020; Zhang et al., 2020b). With the rising trade protectionism and changing geopolitical landscape, the relocation of global production networks and its energy/emissions consequences are increasingly examined (Hoekstra et al., 2016; Jiang and Guan, 2017). This helps to identify barriers and opportunities for sustainable supply chain management. Given the deepening production fragmentation, the production structure of economic systems is studied from the perspective of global value chains to further reveal the determinants of both value creation and environmental impacts in a comprehensive manner (Wang et al., 2021a; Zhang et al., 2021).

The demand-side modelling in SDA has become detailed. As the energy and environmental impacts of consumption as well as investment are increasingly recognized, targeted demand-side measures are urgently needed. To this end, the production activities and

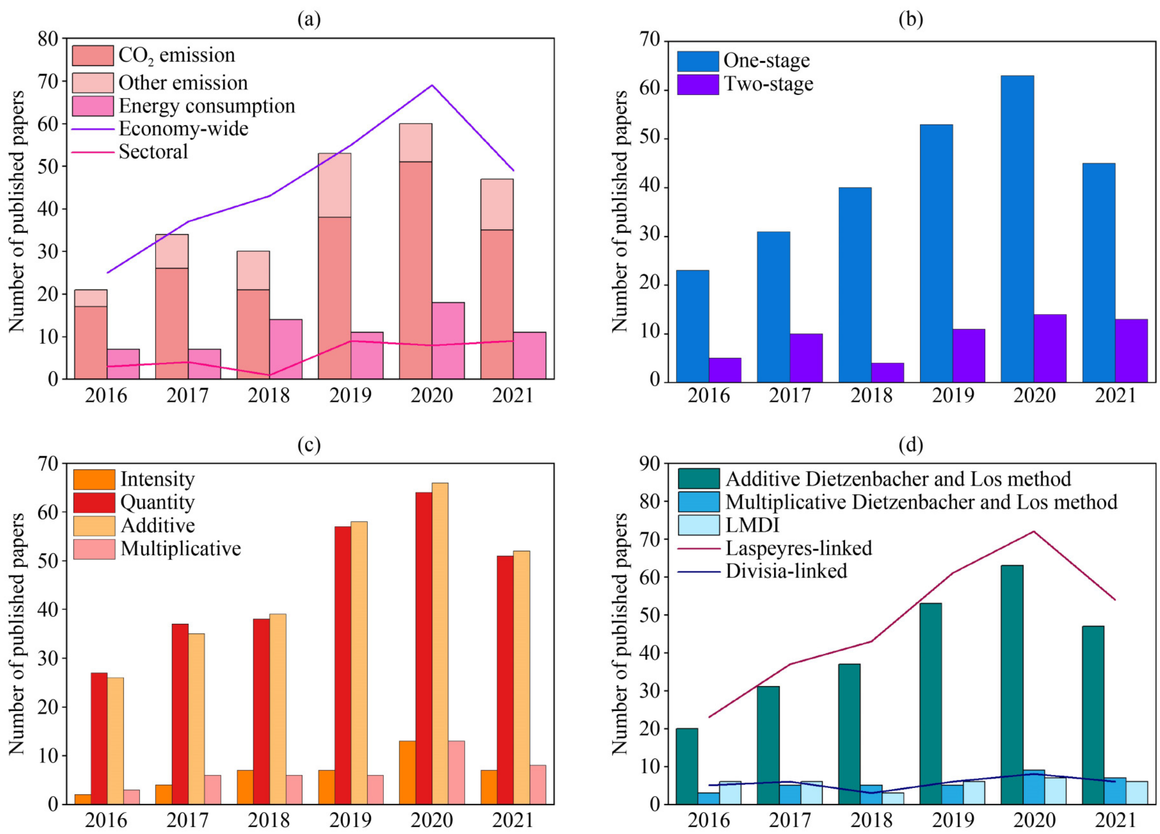

Fig. 4 Methodology and application features of SDA studies, 2016–2021: (a) Total number of SDA studies involving both energy/emissions and at economy-wide/sectoral level; (b) number of studies by one-stage and two-stage decomposition; (c) number of studies by aggregate indicator and decomposition form; (d) number of studies by decomposition methods.

associated energy/emissions induced by particular types of demand, e.g., consumption (Zhang et al., 2016; Duarte et al., 2021), investment (Södersten et al., 2018; Kobayakawa, 2022), and domestic/foreign components (de Vries and Ferrarini, 2017; Chang and Han, 2022), are examined separately. With the rapidly changing population structure, household consumption and embodied energy/emissions are further scrutinized with various demographic features, e.g., urban and rural (Zhang et al., 2016), income (Duarte et al., 2021) and age (Shigetomi et al., 2019). Moreover, to integrate the supply-side and demand-side efforts, the sourcing structure of demand can be disaggregated to track supplier pattern changes (Kaltenegger et al., 2017). These extensions reveal the structural changes in consumption preferences, which offers insights into policy formulation regarding green consumption and investment.

SDA studies have been refined with higher-resolution data. For the temporal dimension, conventionally IO tables are only available for some individual years. To scrutinize the changing patterns of economic systems, annual IO datasets are compiled at national (Su and Thomson, 2016), regional (e.g., Asian Development Bank (ADB)-Multiregional Input–Output Table (Mariasingham, 2015) and European Multiregional Input–Output Table (European Commission JRC, 2020)) and global (e.g., World Input–Output Database (Timmer et al., 2015), Eora (Lenzen et al., 2012; 2013), and EXIOBASE (Tukker et al., 2013)) levels, which facilitate the chaining decomposition. Also, the IO data that are usually lagged can be updated to recent periods (Wei et al., 2020), which makes SDA analysis more timely. Further to the yearly IO data, the granularity of IO tables can be improved, e.g., to a monthly basis (Su and Ang, 2022), to study the dynamics of energy and emissions in a more detailed manner. For the spatial dimension, conventional country-level IO tables are extended to finer geographic scales, e.g., province (Fan and Fang, 2020) and city (Li et al., 2018), to derive detailed assessments. Going a step further, sub-national datasets can be linked to global multiregional input–output tables to study both the intra/inter-national patterns of energy and emissions (Mi et al., 2017). For the sectoral dimension, a single aggregate sector in IO tables can be split to reveal differences in production technology and emission performance across subsectors (Ma et al., 2019). Also, the modelling of energy sectors in IO tables can be augmented with physical data on energy flows and transformation processes, which helps to look into energy-economic system changes in greater details (Guevara and Domingos, 2017).

4.3 PDA

Within the production theory framework, PDA focuses on the technology-related impacts on energy and emissions from a production systems perspective (Zhou and Ang, 2008). To perform the decomposition, entities' technical performances in production and energy/emissions need to be first measured, which is usually estimated using the nonparametric frontier approach (Pasurka, 2006). The decomposition results therefore capture the impacts of both energy/emissions and productive technologies. Determinants of the productive performances, e.g., allocation of and substitution between inputs, can be further studied with two-stage decomposition on the potential activity intensity. In calculation, two main decomposition methods used for PDA are direct decomposition and generalized fisher index, only the latter of which is applicable to the two-stage decomposition. Prior to 2015, PDA is mainly applied to assess economy-wide technological impacts on energy and emissions at country level.

Since 2016, PDA studies have tripled, as shown in Fig. 5(a). While economy-wide studies, especially for China, dominating this area, analyses at the regional, sectoral, and plant levels have emerged. Figure 5(b) further suggests that emission studies have become the majority. Proposed in 2017, the additive PDA studies have grown and accelerated in recent years, though still less than the multiplicative decompositions (Fig. 5(c)). As to the decomposition methods, LMDI has been increasingly penetrated into the PDA literature, despite the conventionally used direct decomposition and generalized fisher index, as shown in Fig. 5(d).

Several new developments of the PDA literature over 2016–2021 are found. As a foundation of the PDA technique, the measurement of technical performance has been largely improved. First, the modelling of production technology better reflects the reality. Rather than the traditional assumption of mutual independence between inputs and outputs, the principle of material balance is adapted in PDA models to rationalize the environmental outcomes from the production process (Wu et al., 2020; 2022). To characterize the negative behavior of emission mitigation by reducing production, the natural disposability of inputs and outputs is applied to the PDA studies (Sueyoshi et al., 2019). To reflect the possibly varying scale efficiency in production, the non-increasing and variant returns to scale assumptions are adopted in PDA models beyond the usual constant returns to scale assumption (Liu et al., 2017; Wang and Feng, 2020). Second, distance functions that measure entities' technical efficiency are improved. Conventionally the Shephard distance function is the most widely used in PDA models,

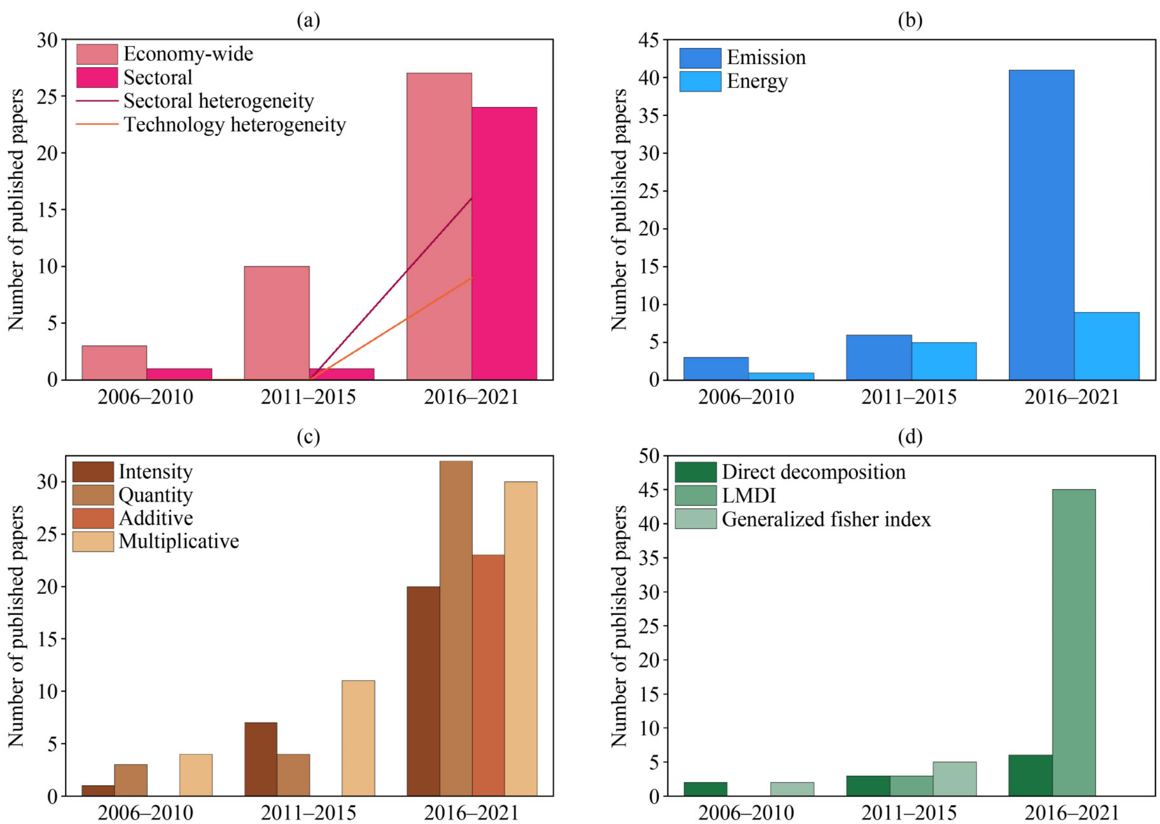

Fig. 5 Methodology and application features of PDA studies, 2006–2021: (a) Total number of PDA studies at economy-wide/sectoral level; (b) number of studies by emissions and energy; (c) number of studies by aggregate indicator and decomposition form; (d) number of studies by decomposition methods.

which can only deal with radial changes in inputs/outputs without proper treatment of undesirable outputs. To overcome these shortcomings, radial and non-radial directional distance functions that allow for reducing undesirable outputs while increasing inputs and desirable outputs are introduced to PDA studies (Chen and Duan, 2016; Wang et al., 2018b; 2019b). This yields a more accurate estimation of technical performance for further PDA decomposition.

Heterogeneities in energy use and emissions have been better modelled with PDA. Energy/Emissions patterns tend to vary across production units in different sectors and regions with different technologies (Wang et al., 2018b). A good understanding of the heterogeneities is necessary for formulating targeted policies. As to the regional and sectoral heterogeneities, when decomposing an aggregate energy/emissions indicator, technical performances of sub-aggregates (e.g., sub-regions and sub-sectors) can be first measured separately, which are then aggregated following the principle of index number theory (Wang et al., 2018b). Examples of studies include Wang et al. (2018b), Tan and Lin (2018) and Xie and Lin (2019). Such studies usually involve multi-level decomposition with disaggregated data, which requires advanced decomposition methods, e.g., LMDI. To account for the technology heterogeneity, the meta-frontier technique is adapted to the PDA modelling (Wang et al., 2019a; Liu et al., 2022). By grouping production entities according to technological features first, entities' technical performances are measured within individual groups and among all entity groups, respectively. The productivity and energy/emissions performances of entities with respect to homogenous peers as well as the technological gaps with respect to the best practice are revealed, based on which the technology heterogeneity and its energy/emissions impacts can be captured. A recent example is Wang and Feng (2020) that tracks the emission consequences of heterogeneities in production technology and energy technology between the heavy and light industries.

The application scope of PDA has been significantly expanded. Further to the traditional economy-wide analyses, PDA empirical studies go deeper to sectoral and firm levels. Examples include PDA applications for food (Xie and Lin, 2019), civil aviation (Liu et al., 2017), manufacturing sectors (Wang et al., 2020), and power plants (Wang et al., 2019a). These studies yield sector- and firm-specific results and thus generate tailored managerial implications. Other than energy use and CO_2 emissions, PDA has increasingly been applied to investigate other issues, e.g., air pollutants (Wang et al., 2021b) and environmentally sensitivity growth (Zhao et al., 2020). Similar to IDA and SDA, PDA is also extended to the spatial dimension to compare regional disparities in energy and emissions (Wang and Zhou, 2018).

5 Trends and features of the decomposition analysis literature

The preceding reveals some key trends and salient features of the decomposition analysis literature since 2016. First, decomposition studies have become increasingly sophisticated. To generate results that are specific with richer policy implications, a growing number of factors appear in decomposition models, even nearly 30 factors used to model energy and emission patterns at finer levels. For example, transformation and distribution of energy are formulated by technologies using multi-level IDA models to assess energy system transition (Mohlin et al., 2019), the energy/emissions cost of a wide variety of trade patterns and demand categories are examined using SDA models with highly disaggregated supply and use data (Wang et al., 2019c; Duarte and Serrano, 2021), and the impacts of resources allocation/substitution and mitigation behaviors in production processes are captured by the two-stage PDA model (Wang et al., 2020). These expansions better characterize the operational features of energy and economic systems in greater details. This is driven by practical needs and accompanied with the available high-resolution data. To inform targeted and tailored policymaking, decomposition analyses that contain more information, better account for heterogeneity and carry more managerial implications are desired. The increasingly advanced digital technologies and data science also boost such analysis (Moran et al., 2020; Qian et al., 2021).

Second, the decomposition techniques tend to converge internally and combine with other modelling approaches. Originally the three decomposition techniques emerge and develop separately with few overlaps (Hoekstra and van den Bergh, 2003; Zhou and Ang, 2008). More recently, particularly since 2016, the similarities and common grounds between them have been increasingly recognized. As to the methodological foundation, the decomposition principles built on the index number theory are found universally applicable to all the three techniques (Wang et al., 2017a). The shared decomposition principles facilitate the convergence between the three techniques in terms of modelling. For example, drawing on the IDA approach, PDA strengthens its modelling of heterogeneity (Wang et al., 2018b), and the modelling of IDA and SDA are linked (Wang et al., 2017c). Largely following the development trend of IDA, the modelling exercises of SDA and PDA extend beyond the traditional temporal analysis to cross-sectional analysis. Also, decomposition methods are commonly applied across the three techniques (de Boer and Rodrigues, 2020). For instance, LMDI that was proposed in the context of IDA has been introduced to SDA and PDA, and the Shapely/Sun method in the IDA literature and the D&L method in

SDA are found identical. On the other hand, the decomposition techniques have been more frequently combined with other approaches. For instance, to test the causality of energy/emissions determinants, decomposition analysis can act as an initial step to isolate the technological and structural impacts, which are then regressed on possible determinants using econometric approaches. Serving as an add-on, the decomposition techniques help to quantify the drivers behind a changing indicator derived from other analytical tools, e.g., the marginal abatement cost curves from energy system modelling (Kesicki, 2013) and emissions paths from scenario analysis (Ang and Goh, 2019). These convergences and extensions address certain methodological limitations of decomposition techniques and further promote their practical usefulness.

Third, the application of decomposition techniques has been largely diversified. With its rising popularity in energy and emission studies, all the three decomposition techniques penetrate to a broader spectrum of environmental and even socioeconomic issues, e.g., land use, water, poverty, inequality, healthcare, and social change. Given the improved modelling and data quality, decomposition analysis also goes deeper and moves from macro-level (e.g., economy-wide and sector) toward micro-level (e.g., firm, plant and household). Adapting the usual temporal studies to a cross-sectional setting yields decompositions along various dimensions such as spatial, scenario and database. Furthermore, traditional decomposition studies that are solely retrospective extend to a prospective perspective that deals with future trajectories of energy use and emissions. These diversifications enrich the application of decomposition techniques and help to understand the dynamics behind energy/environmental/economic issues in a more comprehensive manner, which markedly enhance the practical usefulness of decomposition analysis.

6 Conclusions and outlook

This study provides a systematic literature survey of decomposition analysis applied to energy and emission issues, focusing mainly on the period of 2016–2021. Key journals and articles in this area are identified through a bibliometric analysis of 983 studies published during the six years, which presents the development trends of decomposition analysis literature. The review reveals several new features of decomposition analysis. Generally the decomposition techniques become sophisticated with refined modelling of technologies and economic systems. Convergences among decomposition models/methods as well as couplings with other analytical approaches increasingly appear in the decomposition analysis literature. Accompanied with methodological improvements, the application of decomposition techniques significantly extends toward broader areas, finer disaggregation levels, and diversified dimensions. These academic research progress also enable a wider use of decomposition techniques by governments and international organizations in climate scenarios assessment, emissions mitigation paths planning, policy portfolio formulation and evaluation.

Looking forward, more efforts are needed to advance both the methodology and application of decomposition analysis, and some issues may deserve particular attention. First, it is necessary to establish a generalized and comprehensive methodological framework for decomposition analysis. A more systematic view on decomposition analysis could better clarify the linkages between decomposition techniques and facilitate possible integrations of individual technique's strengths. This also helps to guide application of decomposition techniques. Second, uncertainty needs to be better studied in decomposition analysis. With prospective studies flourishing, decomposition is increasingly performed with respect to projections and scenarios, where uncertainty is an inherent nature and may largely affect decomposition results. Better understanding the role of uncertainty in decomposition thus helps to clarify associated ambiguities and enhance robustness in policy formulation. This requires to develop decomposition models and data analytics tools considering uncertainty as present decomposition is confined to the certainty condition. Third, it is meaningful to accelerate micro-level decomposition analysis. Further to the usual country/sector level studies, assessing energy/emissions patterns at a more micro level (e.g., firm, production line, and equipment) is able to offer more targeted managerial implications and inform actionable measures. However, a key barrier to micro-level studies is usually the lack of data. This could be overcome with the increasingly available high-resolution data (e.g., big data collected from remote sensing, industrial internet and smart meter) in conjunction with advanced data technologies. These issues also present challenges and opportunities for decomposition analysis, and we encourage more studies in these directions.

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