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Invited Review

Data envelopment analysis application in sustainability: The origins, development and future directions

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ABSTRACT

Sustainable development and sustainability assessment have been of great interest to both academe and practitioners in the past decades. In this study, we review the literature on data envelopment analysis (DEA) applications in sustainability using citation-based approaches. A directional network is constructed based on citation relationships among DEA papers published in journals indexed by the Web of Science database from 1996 to March 2016. We first draw the citation chronological graph to present a complete picture of literature development trajectory since 1996. Then we identify the local main DEA development paths in sustainability research by assigning an importance index, namely search path count (SPC), to each link in the citation network. The local main path suggests that the current key route of DEA applications in sustainability focus on the environmental sustainability. Through the Kamada–Kawai layout algorithm, we find four research clusters in the literature including corporate sustainability assessment, regional sustainability assessment, sustainability composite indicator construction, and sustainability performance analysis. For each of the clusters, we further identify the key articles based on citation network and local citation scores, demonstrate the developmental trajectory of the literature, and suggest future research directions.

1. Introduction

The concept of sustainability stems from ecology and describes the use of a regenerative natural system in such a way that this system retains its essential properties and its population can naturally be replenished. In more general terms, sustainability is the endurance of systems and processes. The organizing principle for sustainability is sustainable development, which finds its way into the economics and management areas in 1987 when sustainable development was first initiated as an environmentally friendly, economically feasible and socially acceptable growth pattern in the Brundtland Commission (formally named as the World Commission on Environment and Development (WCED). Since then, thousands of initiatives have been taken at the local, national, and global levels in an attempt to address different aspects of the sustainability challenges (Mebratu, 1998).

Since the early 2000s, firms have been pressured to pay attention to the triple bottom line of sustainability – profit, people and planet (Elkington, 2002) because of the increasing demand for natural resources (clean water, crude oil, woods, metals, etc.) whose supply continues to diminish, the raised concerns about various unethical corporate practices and the development of the emerging markets with supply-chain constraints (Tang & Zhou, 2012). As a result, the need for measuring sustainable development is widely recognized (e.g., Tyteca, 1998). So far, sustainability assessment has served four major purposes: decision making and management, advocacy, participation and consensus building, and research and analysis (Parris & Kates, 2003), and been applied at different levels: national (e.g., Coli, Nissi, & Rapposelli, 2011; Munksgaard, Wier, Lenzen, & Dey, 2005), regional or urban community (e.g., Hu, Sheu, & Lo, 2005; Munda & Saisana, 2011), industry sectorial (e.g., Peres-Neto, Legendre, Dray, & Borcard, 2006; Zofio & Prieto, 2001), and corporate (e.g., Figge & Hahn, 2004; Kuosmanen & Kuosmanen, 2009). In the beginning, sustainability assessment mainly focused on environmental sustainability problems covering only economic and environmental dimensions. More recently, this line of research has started to focus on prospects for lasting net gains and the acceptability of trade-off rules among the environmental, economic and social dimensions (Gibson, 2006; Pope, Annandale, & Morrison-Saunders, 2004; Winfield, Gibson, Markvart, Gaudreau, & Taylor, 2010).

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Accordingly, three categories of indicators and methods for sustainability evaluation have emerged in the literature. *System analysis* is an approach that takes in consideration of both the relationships between the internal components of the system, and the relationships between internal components and external environment (e.g., Antonio, Cristina, & Stefano, 2012; Goerner, Lietaer, & Ulanowicz, 2009; Ulanowicz, 2009). *Flow analysis* evaluates system sustainability through resource utilization efficiency that only considers the relationship between internal components and the external environment (e.g., Balocco, Papeschi, Grazzini, & Basosi, 2004; Campbell & Garmestani, 2012; Paoli, Vassallo, & Fabiano, 2008). Finally, *indicator enumeration* mainly chooses indicators from environmental, economic, social and institutional aspects to evaluate the system sustainability without considering either of the relationships mentioned above (e.g., Ness, Urbel-Piirsalu, Anderberg, & Olsson, 2007; Ou & Liu, 2010; Yli-Viikari, 1999).

Data Envelopment Analysis (DEA) (Charnes, Cooper, & Rhodes, 1978) is a method for evaluating performance of peer decision making units (DMUs) with multiple performance measures that are termed as inputs and outputs. DEA first establishes an 'efficient frontier' formed by a set of DMUs that exhibit best practices and then assigns the efficiency level to other non-frontier units according to their distances to the efficient frontier. Over the years, DEA has been enriched and modified. Numerous DEA models have been developed and used in various applications including sustainability research. In general, there are three approaches to employ DEA models in the sustainability literature (Choi & Zhang, 2011): traditional DEA models with simple translation of data (Lovell, Pastor, & Turner, 1995; Yeh, Chi, & Hsu, 2010), traditional DEA models treating undesirable outcomes as inputs (Hu & Wang, 2006; Zhang, Bi, Fan, Yuan, & Ge, 2008), and DEA models employing the concept of weak disposability technology (Färe & Grosskopf, 2004; Zhou, Ang, & Poh, 2008a). Researchers have applied DEA models to address corporate, regional and national sustainability issues as well as those related to supply chain.

Although DEA has been extensively applied in sustainability, few surveys to the best of our knowledge have been conducted to systematically review the current status of the literature and discuss the future research direction except for Dakpo, Jeanneaux, and Latruffe (2016). Although Dakpo et al. (2016) make a critical review on methods integrating environmental aspects into productive efficiency, their study focuses on only environmental factors, especially the undesirable outputs in production technology modeling, and does not include social factors, another important part of sustainability. In addition, their review is based on subjective and qualitative analyses rather than objective quantitative analysis methods. To fill the gap, our study collects 320 relevant papers published from 1996 to March 2016 and analyzes the research status of DEA applications in sustainability through citation analysis of bibliometrics. Using the citation analysis software HistCite, we conduct a visual analysis and construct a citation chronological graph to identify the main development route and key publications of DEA application in sustainability. Then with the help of Pajek software, we discover the major research clusters as well as the local main paths, and further identify future research directions in each research cluster. In addition, our review highlights the importance of reliable sustainability measures and introduces current major DEA approaches in sustainability evaluation.

This paper is organized as follows. In the next section, we describe the data and methods used in this study. Section 3 discusses the basic statistics for the DEA applications in sustainability. Section 4 presents the major findings through citation chronological graph and main path analysis. Section 5 identifies the major research clusters and draws the development trajectories of each cluster, which presents the most-cited works in each research area. The last section draws conclusions including implications and insights from the analysis results.

2. Review methods

2.1. Data source and collection

To facilitate a coherent review, we use systematic searches and formal summaries of the literature to integrate major studies in the area. ISI Web of Science (WOS) is used as the data source to collect relevant scholarly work. WOS is the world's leading citation database with a multidisciplinary coverage of over 10,000 high impact journals in science and social science as well as proceedings of over 120,000 international conferences. Specifically, we select the databases within WOS including Science Citation Index Expanded (SCIE), Social Sciences Citation Index (SSCI), Conference Proceedings Index-Science (CPI-S), and Conference Proceedings Index-Social Science and Humanities (CPI-SSH).

We start with an exhaustive search in the databases using combinations of sustainability related keywords (i.e., sustainability, sustainable, green, and social responsibility) with the term of DEA or data envelopment analysis in the fields of title, abstract, author keyword, or Keywords Plus®. A sample of 475 articles is retrieved from the databases after the initial search. We then read through these papers' abstracts to assess whether they dealt with DEA applications in sustainability. When we are unsure, we download and read the full publications. Non-DEA or non-sustainability papers are manually examined and excluded from the dataset. In the course of manual checking and screening, we find out that some papers, although listed as DEA or sustainability in the Keywords Plus® field, contain limited contents about DEA or sustainability For these cases, we conduct a partition analysis on the citation network to find out the outliers and then remove them from the dataset. After the manual checking and screening, the final sample consists of 320 articles published from 1996 to March 2016 in various subject areas including corporate sustainability assessment, sustainability composite indicators construction, sustainability performance analysis, and regional sustainability development assessment. Out of the 320 articles, 120 were published in journals with a 2015 ABS (Chartered Association of Business Schools) journal ranking of 3 or above. We then developed a detailed summary for each article in the final sample.

2.2. Citation-based review methods

To further probe the origins and current state of the literature, we employ two citation-based methods: the main path analysis and Kamada–Kawai algorithm. We believe these citation-based methods can complement to the traditional qualitative review methods by bringing a level of objectivity and quantification. In recent years, the citation-based methods have been applied increasingly across a variety of research fields such as literature research (Liu, Lu, Lu, & Lin, 2013), journal evaluation (Garfield, 1972), and scholar assessment (Schildt, Zahra, & Sillanpää, 2006).

The main path analysis, introduced by Hummon and Doreian (1989), is a well-known method that traces the main knowledge flow in a scientific discipline through citation data. This network-based method treats scientific publications as nodes of a network. Then, citation information is used to establish links among nodes, and a link's direction points from the cited document to the citing one. The first step in finding the main path is to identify the importance of each citation link in the network, which can be measured by counting the times a citation link has been traversed. In this study, we choose to use the search path count (SPC) recommended by Batagelj (2003) to do the counts. The SPC for each link is defined as the total number of times a link is

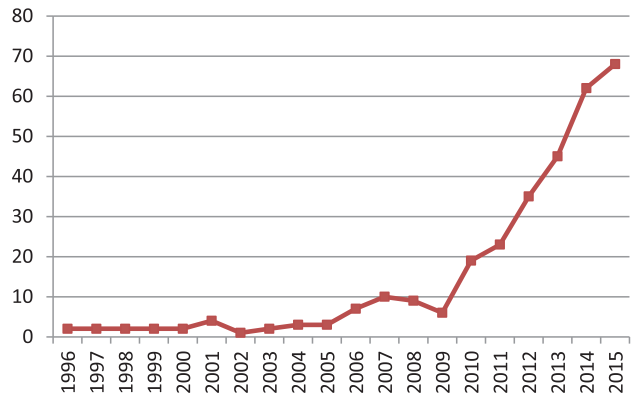

Fig. 1. Distribution of publications over time.

traversed assuming that one exhausts all efforts in searching out all paths from all the *sources* (nodes that are cited, but cite no other nodes) to all the *sinks* (nodes that cite other nodes, but are not cited). After SPCs for all the links are calculated, we start the main path search from all the sources by applying the "priority first search" algorithm as Hummon and Doreian (1989) suggested. That is, at any node, one always chooses the next link in the path with the highest SPC as the outgoing link. By applying the choice rule repeatedly until hitting a sink, a main path is constructed.

Another citation-based method used in this study is Kamada–Kawai algorithm, an automatic graph drawing algorithm based on the idea that graph can be considered as a dynamic system of *springs*. In that system, every pair of nodes, which is connected by edge, is connected by spring. The optimization procedure tries to minimize the total energy of the system using the two-dimensional Newton–Raphson method, which is known in the multidimensional scaling (MDS) community as *the stress function*. The strength of a spring between two vertices is inversely proportional to the square of the shortest distance (in graph terms) between those two vertices. Essentially, vertices that are closer in the graph-theoretic sense (i.e., by following edges) will have stronger springs and therefore be placed closer together. An advantage of this method is that it can be applied straightforwardly to drawing edge-weighted graphs (Harel & Koren, 2002).

3. Literature overview

3.1. Publications over time

Fig. 1 demonstrates the number of publications per year from 1996 to 2015. The literature of DEA application in sustainability can be traced back to the year of 1996 when Färe et al. first introduced input-orientated DEA methods containing "bad output" pollution variables to obtain environmental performance indicators for US fossil fuel-fired electric utilities. Since then, DEA has found its way into a broad spectrum of applications in the sustainability area such as energy and environment efficiency (Sueyoshi & Goto, 2014a, b; Zhang et al., 2008), and corporate social responsibility (Chen & Delmas, 2011). The number of publications has been flourished in the past five years. The recent increased interest in this area may be due to the 2009 United Nations Climate Change conference, commonly known as the Copenhagen Summit, which raised climate change policy to the highest political level, and therefore drew attention of the academe to the issue of sustainability.

3.2. Publication outlets and scholarly community

Approximately half (48%) of the reviewed articles were published in 20 journals (see Fig. 2) and these journals present a wide range of research scope from specialized journals in energy and environment journals to general operational management journals. Among the 20 journals, seven journals published at least 10 articles, including Energy Economics, Journal of Cleaner Production, Energy Policy, Sustainability, Ecological Economics, Applied Energy, and European Journal of Operational Research.

Table 1 lists the top 10 DEA authors in order according to the total local citation scores of their published papers in sustain-

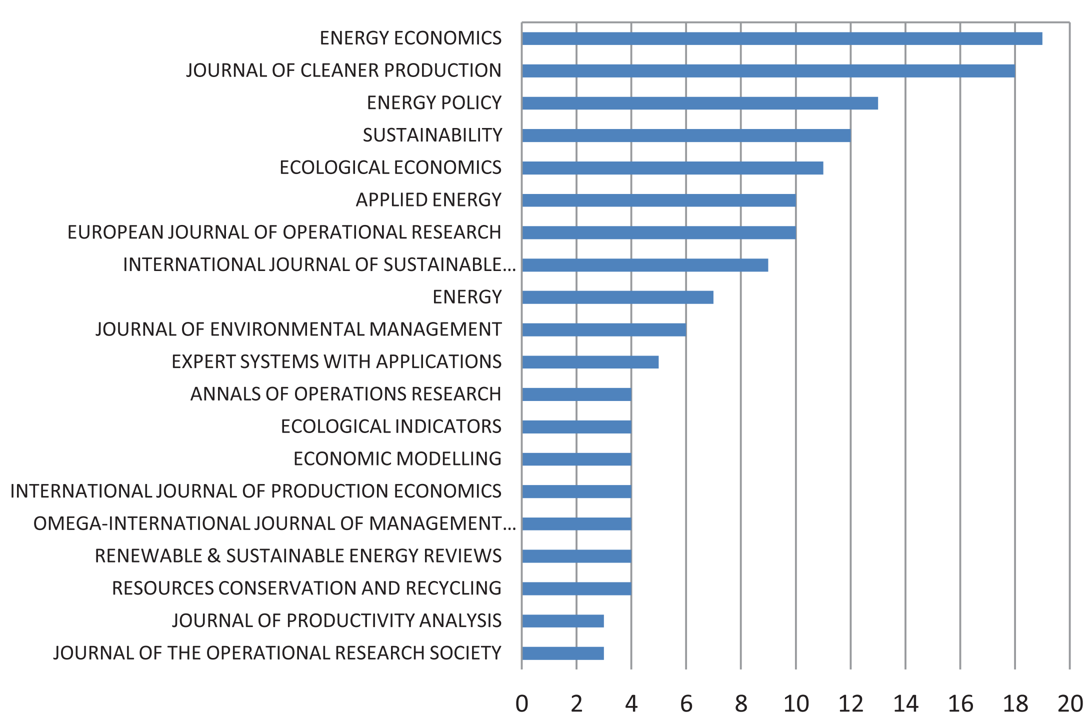

Fig. 2. Distribution of reviewed papers among top 20 journals.

Table 1
Top 10 DEA researchers in sustainability area according to their total LCS.

Ranking	Authors	Total LCS	Total number of papers
1	Zhou	117	7
2	Ang	100	5
3	Sueyoshi	91	14
4	Färe	66	4
5	Grosskopf	66	4
6	Poh	63	2
7	Goto	54	7
8	Tyteca	49	3
9	Chung	37	1
10	Zhang	36	2

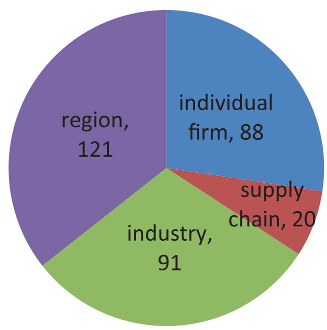

Fig. 3. Distribution of reviewed papers using different analysis units.

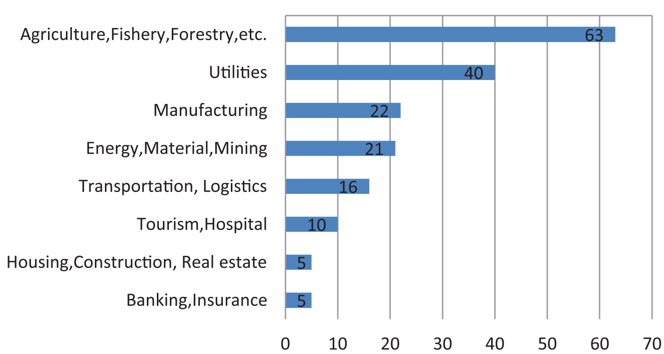

Fig. 4. Distribution of reviewed papers by industry sector.

ability area. Local citation score (LCS) is based on total citations of paper A received from local collection, and shows the citation frequency within the collection, which can indicate the relative importance of certain paper. In this study, we calculate a researcher's total local citation score (TLCS) as the sum of LCS of his/her all papers. The TLCS can reflect the relative importance of the researcher in certain area. As can be seen from the table, Zhou, Ang, Sueyoshi, Färe and Grosskopf are the top five DEA researchers in sustainability area based on the TLCS.

3.3. Research analysis unit and application area

When analyzing the content of the 320 articles, we divide the publications into four categories based on the unit of analysis: individual firm, supply chain, industry, and region. Fig. 3 is the breakdown pie chart of the number of papers in each category. We find that a majority (56%) of the reviewed studies focus on corporate sustainability and industrial sustainability using firms as DMUs. On the other hand, a growing attention has been given to sustainability issues in different stages along the supply chain. There are also 121 papers studying regional sustainability from the macro-level perspective. The region here can be a city, a province or a country.

Table 2
Distribution of reviewed papers in different DEA method groups.

Research methodology	Number of papers
Traditional DEA	92
SBM and intertemporal DEA	61
Extending models	51
Two-stage contextual factor evaluation framework	40
Special data	13
Two-stage Network DEA	14
Others	62

In Fig. 4, we list various industry sectors studied by at least 5 reviewed papers. The top five most frequently studied industries include Agriculture, Utilities, Manufacturing, Energy, Transportation and Logistics. It is not surprising because these industries have significant impacts on environmental and social sustainability.

3.4. DEA methodologies employed

The majority of the reviewed papers focus on analytical models, and a variety of DEA methods have been applied in developing these models. Based on Liu et al. (2013, 2016) and Zhou, Ang, and Poh (2008b), we classify DEA methods used in the sustainability research into six main groups: ① Traditional DEA models including CCR and BCC models; ② Slack-based models (SBM) and intertemporal DEA models, especially DEA-based Malmquist productivity index; ③ Extending models including assurance region, dual factor, cross-efficiency and super-efficiency; ④ Two-stage contextual factor evaluation framework that first obtains efficiency scores through DEA analysis and then correlates these scores with various contextual factors either by ordinary least squares regressions (OLS), Tobit regressions, or maximum likelihood estimation (MLE) etc. ⑤ Models handling special types of data such as fuzzy, ordinal, qualitative, negative data and so on; ⑥ Two-stage network DEA. Table 2 presents the number of studies in each method category.

As Table 2 shows, the most frequently used DEA methods in sustainability study are Traditional DEA models (e.g., CCR and BCC models). Typically, traditional DEA models use the radial measure and calculate efficiency based on the input excesses and output shortfalls. Recently, more and more advanced DEA models (those in Categories 2–6) have been developed and applied in sustainability research in response to the growing demand for analysis accuracy and data complexity.

Among those advanced methods, SBM and intertemporal DEA (Category 2) are the most popular ones used in a total of 61 studies. SBM introduced by Tone (2001) has been frequently used to evaluate the sustainability of DMUs at both the micro and macro levels by including undesirable outputs in the model (Chen & Xie, 2015; Goto, Otsuka, & Sueyoshi, 2014). Recently, new SBM models are also developed, for example, SBM based on directional distance functions (Färe & Grosskopf, 2010), sequential slack-based efficiency measure (SSBM) (Zhang & Kim, 2014). Intertemporal DEA, on the other hand, employs the Malmquist model to handle dynamic time series data, and has been widely applied in evaluating the intertemporal sustainability performance of both corporations (Graham, 2009) and regions (Lei, Zhao, Deng, & Tan, 2013).

Extending DEA models (Category 3) are the second popular advanced DEA methods used in sustainability study. As an extension to conventional DEA models, this group methods include assurance region on multipliers (Wey, 2015), dual factor handling the case where factors simultaneously play both input and output roles (Kumar, Jain, & Kumar, 2014; Mirhedayatian, Azadi, & Saen, 2014), cross-efficiency DEA for peer evaluation (Lee & Saen, 2012), and super-efficiency DEA for further ranking the efficient DMUs (Li & Lin, 2015b).

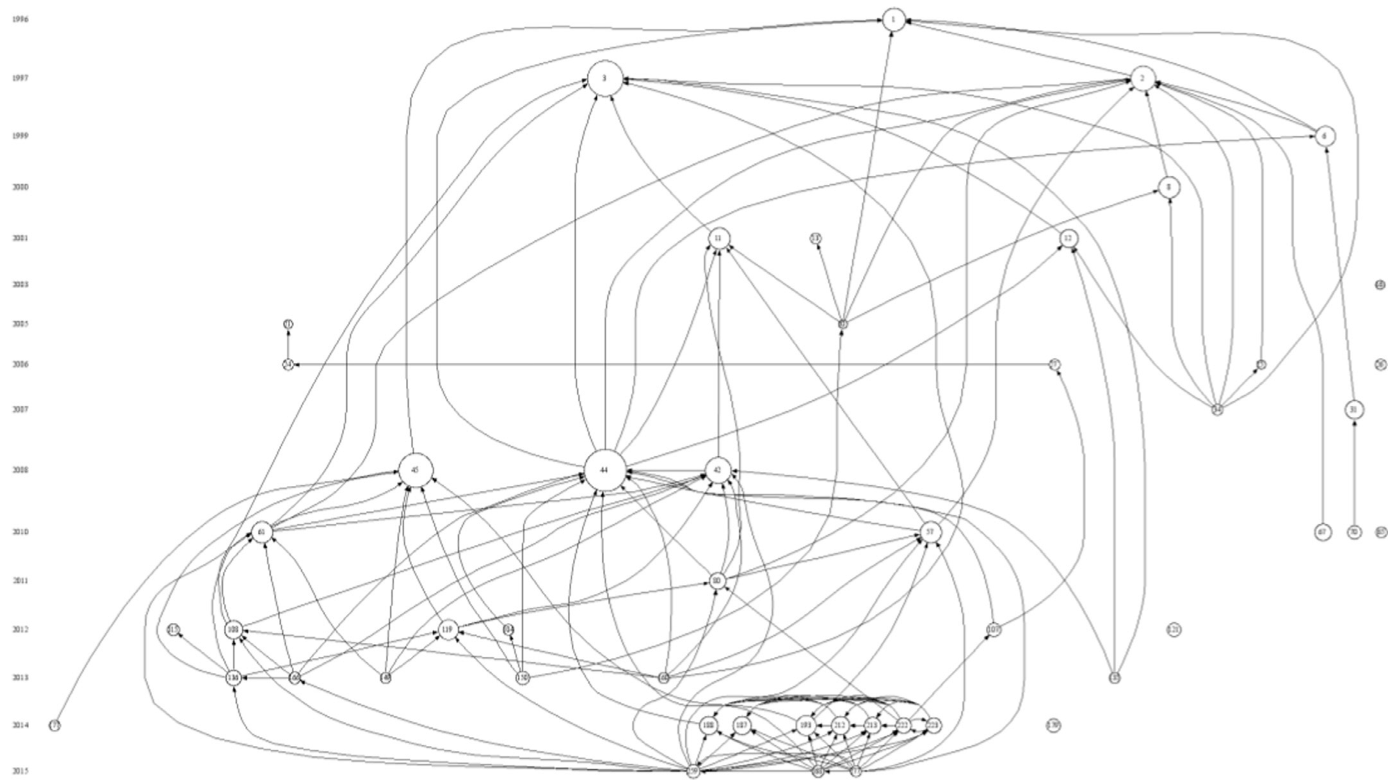

Fig. 5. Citation chronological graph of DEA papers in sustainability (LCS-count50).

Two-stage contextual factor evaluation framework (Category 4), introduced by Simar and Wilson (2007), also get widely used in sustainability analysis. This framework usually obtains the efficiency scores through DEA methods first, especially using bootstrapping methods to construct a base for statistical inference, and then conducts contextual factor analysis through a series of statistical regression analyses. The purpose of this line research is to find the determinants and influential factors of sustainability, or to portray the relationships between sustainability and environmental factors (Assaf, Josiassen, & Cvelbar L, 2012; Chen, Cook, Kao, & Zhu, 2014; Gadanakis, Bennett, Park, & Areal, 2015; Picazo-Tadeo, Gómez-Limón, & Reig-Martínez, 2011).

DEA methods in Categories 5 and 6 have not been extensively employed in sustainability studies. But recently, more and more attention has been given to models handling special types of data in sustainability research, including fuzzy data (Azadi, Jafarian, Saen, & Mirhedayatian, 2015), ordinal data (Chen & Delmas, 2011), qualitative (Zeydan, Çolpan, & Çobanoğlu, 2011), negative data (Dimaria, 2014) and so on. Two-stage network DEA is also gaining popularity, which takes into account the inner operational mechanism of the subsystems in each DMU under evaluation (Chen et al., 2012).

In addition to the six major categories of DEA methodologies, several new trends are observed in the literature. First, our literature review reveals that two or more DEA methods could be used simultaneously in one study. Second, in sustainability evaluation, the concept of material balance is being incorporated into the production model (Coelli et al., 2007). Last, recent research has been combining DEA methods with more non-DEA methods such as analytic hierarchy process (AHP) (Wey, 2015), principal component analysis (PCA) (Dong et al., 2015), analysis of variance (ANOVA) (Kim et al., 2011), artificial neural network (ANN) (Chuang, Chang, & Lin, 2011), and hierarchical clustering method (Xie, Zang, & Qi, 2016).

4. Citation chronological graph and local main path analysis

In this section, we present our major findings through the citation based methods. Among the 320 reviewed articles, we first identify the top 50 papers with the highest local citation scores (LCS). Then, based on the top 50 papers, we draw a citation chronological graph that provides the foundation for the local main path analysis on the development trajectory of the research contents.

4.1. Findings from citation chronological graph

The citation chronological graph indicates all important papers during the development of a discipline and their relationships based on citations during the active years. Using Histcite software, we draw the citation chronological graph of the top 50 DEA publications in sustainability (see Fig. 5). In the figure, a circle represents a paper with its serial number inside and the circle size reflects its LCS value. The bigger the circle is, the higher the paper's LCS is, and the more significant it is. The arrow indicates the direction of citation, from a citing paper to a cited paper. The ordinate is a timeline from 1996 to 2015.

In Fig. 5, there are a total of 141 links between the 50 nodes (major papers). As we can see, the DEA application in sustainability research begins with Färe, Grosskopf, and Tyteca (1996). But, the number of citations is small in the early years. Papers with more citations have been published since 2008, which shows that the DEA application research in sustainability area has become more and more popular recently. The review paper by Zhou et al. (2008b) has the maximum LCS value of 52, which provides a good summary on previous DEA applications in energy and environment efficiency assessment as well as a reference for future sustainability research. The paper with the second highest LCS value of 37 is (Chung, Färe, & Grosskopf, 1997) that proposes a new

Table 3
Detailed information of the studies in the local main path.

ID	Title	Authors	Journal	Year
1	An activity analysis model of the environmental performance of firms—application to fossil-fuel-fired electric utilities	Färe, Grosskopf, Tyteca	Ecological Economics	1996
2	Linear programing models for the measurement of environmental performance of firms—concepts and empirical results	Tyteca	Journal of Productivity Analysis	1997
6	Towards indicators of sustainable development for firms: a productive efficiency perspective	Callens, Tyteca	Ecological Economics	1999
44	A survey of data envelopment analysis in energy and environmental studies	Zhou, Ang, Poh	European Journal of Operational Research	2008
42	Linear programing models for measuring economy-wide energy efficiency performance	Zhou, Ang	Energy Policy	2008
57	Total factor carbon emission performance: a Malmquist index analysis	Zhou, Ang, Han	Energy Economics	2010
80	Evaluation of potential reductions in carbon emissions in Chinese provinces based on environmental DEA	Guo, Zhu, Fan	Energy Policy	2011
119	Efficiency and abatement costs of energy-related CO_2 emissions in China: a slacks-based efficiency measure	Choi, Zhang, Zhou	Applied Energy	2012
136	Energy and emissions efficiency patterns of Chinese regions: a multi-directional efficiency analysis	Wang, Wei, Zhang	Applied Energy	2013
166	China's regional energy and environmental efficiency: a range-adjusted measure based analysis	Wang, Lu, Wei	Applied Energy	2013
259	China's regional sustainability and diversified resource allocation: DEA environmental assessment on economic development and air pollution	Sueyoshi, Yuan	Energy Economics	2015a
268	Environmental assessment on coal-fired power plants in US north-east region by DEA non-radial measurement	Sueyoshi, Goto	Energy Economics	2015a
277	DEA environmental assessment in time horizon: radial approach for Malmquist index measurement on petroleum companies	Sueyoshi, Goto	Energy Economics	2015b
291	Japanese fuel mix strategy after disaster of Fukushima Daiichi nuclear power plant: Lessons from international comparison among industrial nations measured by DEA environmental assessment in time horizon	Sueyoshi, Goto	Energy Economics	2015c
290	Comparison among US industrial sectors by DEA environmental assessment: Equipped with analytical capability to handle zero or negative in production factors	Sueyoshi, Yuan	Energy Economics	2015b
305	Marginal rate of transformation and rate of substitution measured by DEA environmental assessment: comparison among European and North American nations	Sueyoshi, Yuan	Energy Economics	2016

index called the Malmquist–Luenberger productivity index which overcomes the shortcomings of the original Malmquist index. The Malmquist–Luenberger index readily allows for inclusion of undesirable outputs without requiring information on shadow prices. Zhang et al. (2008) is another highly cited paper with a LCS value of 34, which analyzes eco-efficiency of industrial system using DEA, introduces the concept of industrial system eco-efficiency, and invites many researchers into the regional sustainable development assessment area. It is noteworthy that there are some nodes isolated or with fewer links away from the main stream, which may indicate some interesting research areas that have not been well developed. To further refine the research topic and the development process, we next employ the local main path analysis.

4.2. Findings from local main path analysis

The local main path indicates the most significant knowledge route at each juncture of knowledge dissemination for a scientific discipline (Liu et al., 2013). Using Pajek software, we identify the local main path in the literature, and present it in Fig. 6. In the figure, the arrow indicates the direction of knowledge flow from the cited publication to the citing one, and the line thickness reflects the search path count (SPC) value. The thicker the line is, the more significant the route is.

The local main path consists of 16 papers, which constitute the backbone of the whole network and play an important role in knowledge flow of the field. Table 3 lists the 16 papers in detail.

The origin of the local main path starts with Färe et al. (1996), in which the environmental performance concept is first proposed. It uses input-orientated DEA methods containing "bad output" pollution variables to evaluate environmental performance in a similar manner to the earlier hyperbolic DEA methods used by Färe, Grosskopf, Lovell, and Pasurka (1989), and introduces the weak disposability concept to account for the fact that the bad outputs (pollution) cannot be freely disposed, thereby laying out the foundation of DEA environmental sustainability evaluation for future research. Following Färe et al. (1996), Tyteca (1997) uses three different DEA models – undesirable output-oriented DEA model, both inputs and undesirable outputs oriented DEA model, and output oriented DEA model to calculate environmental performance indicators, and illustrates the approaches by using the same data set as Färe et al. (1996). Their results show that different decision makers (e.g., a public decision-maker vs. company's manager) should choose different DEA models in accordance with their purposes when evaluating environmental performance. The third paper on the path Callens and Tyteca (1999) first propose the evaluation of corporate sustainability using DEA methods. In comparison with prior studies on environmental performance evaluation that only focus on economic and environmental dimensions, their study points out three-way efficiency (economic, social and environmental) as a necessary (but not sufficient) step towards sustainability. Zhou et al. (2008b) make a literature review on the application of DEA in energy and environmental (E&E) issues over the period of 1983–2006.

The next two papers on the local main path are still in the research stream of energy and environmental efficiency. Zhou and Ang (2008b) fill the gap by evaluating energy efficiency within a joint production framework of both desirable and undesirable outputs. Zhou, Ang, and Han (2010) extend CO_2 emission performance research from cross-sectional to time-series analysis by introducing a Malmquist CO_2 emission performance index (MCPI). They further propose bootstrapping MCPI for sensitivity analysis and statistical inferences, and make a multiple regression analysis, which invites more and more studies to use the two-stage contextual factor evaluation framework. Guo, Zhu, Fan, and Xie (2011) further use the similar DEA methods to compute potential

Fig. 6. Local main path of DEA application research in sustainability.

carbon emission reductions for energy conservation technology (ECT) and energy structural adjustment (ESA).

Most of the studies prior to 2012 use the radial efficiency measures that cannot capture all the technical inefficiency. To fill the gap in the literature, a group of different DEA models have been developed recently. For example, Choi, Zhang, and Zhou (2012) employ a slacks-based efficiency measure, which measures all the slack variables of inputs and outputs and can find out all the sources of inefficiency. Wang, Lu, and Wei (2013) utilize the multi-directional efficiency analysis (MEA) approach proposed by Bogetoft and Hougaard (2004). MEA selects benchmarks such that the input contractions or output expansions are proportional to the potential improvement in each input or output variable separately, so that not just the efficiency status but also the efficiency patterns can be detected. In the next paper, Wang, Wei, and Zhang (2013) apply the Range-Adjusted Measure based DEA (RAM-DEA) models proposed by Cooper, Park, and Pastor (1999) and combine both energy performance and environmental performance for each DMU under a unified treatment in order to measure China's regional integrated energy and environmental efficiency.

The more recent references on local main path, conducted by Sueyoshi and his group, are mainly about sustainability evaluation in the context of natural and managerial disposability. Sueyoshi and Yuan (2015a) are the first to discuss the radial measurement of scale efficiency under the natural and managerial disposability concepts. They also change the research direction to China's environmental pollution measured by $PM_{2.5}$ and PM_{10} instead of CO_2. Afterwards, Sueyoshi and Goto (2015a) measure the scale efficiency by two non-radial models and examine the influence of the small number ε on unified and scale efficiencies for the first time. After Sueyoshi and Yuan (2015a) and Sueyoshi and Goto (2015a, b, c) are a series of studies integrating time horizon into the analysis. By incorporating Malmquist index into the proposed DEA environmental assessment and linking the index to natural and managerial disposability, these two papers examine the occurrence of frontier shifts over time. Sueyoshi and Goto (2015b) employ a radial approach, while Sueyoshi and Goto (2015c) use non-radial models to handle zero and negative data points. Furthermore, Sueyoshi and Yuan (2015b) extend the work of Sueyoshi and Goto (2015c) by proposing a new DEA approach to handle zero and negative values for both the radial and non-radial measurements, which discompose the negative desirable output into positive and negative parts. Sueyoshi and Yuan (2016a) discuss a new use of DEA environmental assessment to measure Marginal Rate of Transformation (MRT) and Rate of Substitution (RS) among production factors. Traditionally, MRT and RS measurements are subject to the problem of instability caused by multipliers or dual variables. To overcome the problem that, this study, for the first time, applies a new multiplier restriction method into the assessment.

The local main path analysis shows that the current key route of DEA application in sustainability focuses on environmental sustainability: namely, how to minimize the negative influence on the environment while maximizing economic outputs. Along the local main path, research topics have evolved from sustainability evaluation to sustainability improvement; research methods have extended from radial approaches (hyperbolic DEA) to non-radial ones; research perspectives have changed from static to intertemporal analysis; and research scenarios have extended from the weak disposability to the natural and managerial disposability. More recent development of the literatures starts to evaluate scale efficiency in the sustainability context with some special models aimed at handling special types of data. Multiplier restriction is also adapted into sustainability evaluation. In addition, the significance of specific parameters used in DEA models has been discussed including the non-Archimedean small number and the type of Damages to Return (DTR), Returns to Scale (RTS), and Damages to Scale (DTS).

Although many topics and methods have been examined, all of the studies along the local main path focus on the environmental aspect of sustainability. The other two major components of sustainability triple bottom line—*economic* and *social* sustainability seem under investigated in the literature. In particular, there is a lack of studies evaluating interactive impacts between the three components (i.e., *social-environmental*, *environmental-economic*, and *social-economic*) on sustainability issues. In addition, several methodological challenges remain and call for further exploration such as time lag between inputs and their effects, structural differences among industries when evaluating regional sustainability, self-sufficiency rates in energy supply of nations, occurrence of multiple solutions, and future uncertainty and so on.

Because the local main path selects the route with the highest SPC value at every branching point, some important works may be missing from this path. In the following section we adopt a different citation-based method—Kamada–Kawai algorithm to draw

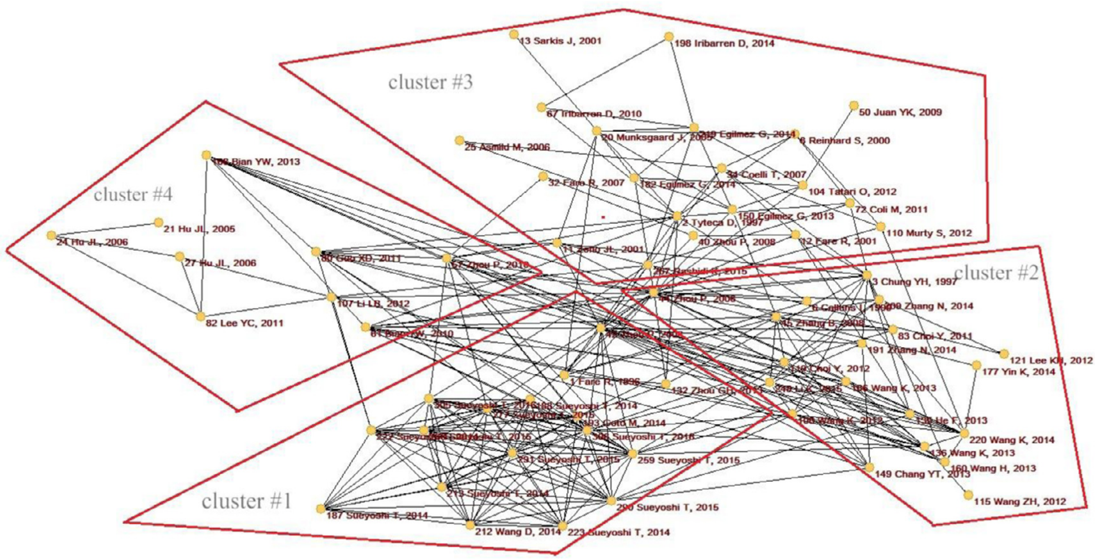

Fig. 7. Citation network graph.

Table 4
Research topic clusters.

Cluster	Research topic	Main research content
1	Corporate sustainability assessment	Measure corporate eco-efficiency and social performance using different DEA methodologies
2	Sustainability composite indicators construction	Methodology development of DEA in sustainability composite indicator, mainly in macro level
3	Sustainability performance analysis	Analyzing the impact factors of sustainability, and the relationships of different sustainability dimensions
4	Regional sustainability development assessment	Evaluate the sustainability of regional development using various DEA models based on energy usage and resource usage

the whole picture of the citation network and identify research clusters accordingly.

5. Research topic clusters

Using Kamada–Kawa algorithm in Pajek software, we construct the citation network and then identify research clusters of DEA applications in sustainability. We first delete those vertices with an input degree of 1 or less[1] to select the significant papers. After this operation, we get a new network with 65 significant papers. Then we use Kamada–Kawa algorithm to draw the layout of their citation network (see Fig. 7). The arrows indicate the direction of citations, and the solid circles represent published papers with a serial number, author name(s) and published year beside it. The citation network is divided into four research topic clusters by Kamada–Kawa algorithm as listed in Table 4: (1) corporate sustainability assessment, (2) sustainability composite indicators construction, (3) sustainability performance analysis, and (4) regional sustainability development assessment.

Before moving to each specific research topic cluster, it is worthy of pointing out that knowledge exchange and connections exist between clusters. Much of the knowledge exchange occurs between sustainability composite indicator construction (Cluster 2) and the application of such indictors in sustainability assessment. For example, Zhang et al. (2008) connects Clusters 1 and 2 by making the DEA methods for constructing sustainability composite indicators be applied to corporate sustainability assessment. Egilmez, Kucukvar, and Tatari (2013) is an important node publication connecting Clusters 1 and 3 by extending the sustainability assessment to the impact factors analysis of sustainability. Some seminal works could connect all four research clusters such as Färe et al. (1996) and Zhou et al. (2008b).

In the successive sections, we will summarize the major findings in each of the research topic clusters as well as make suggestions on future research directions.

5.1. Corporate sustainability assessment

5.1.1. Current status of the literature

The corporate sustainability assessment is perhaps the most popular DEA application in sustainability research. This is evident by the number of corporate sustainability assessment papers published. In this research topic, scholars use various DEA models to measure the eco-efficiency or corporate social responsibility (CSR) to support the decision-making process of corporations. Table 5 lists the indicators usually used as DEA inputs and outputs for firm DMU evaluation.

From Table 5, we can find that the commonly used indicators for corporate economic inputs include assets, capital and various cost-related indicators at the firm level. The most frequently used environmental input is energy consumption, then comes to land use and investment for environment protection. Carbon footprint, as a measure of the total amount of carbon dioxide, nitrogen oxides, and methane emissions from fossil fuel combustion, is newly adopted indicator by researcher. In social dimension, the most frequently used input indicator is human labor. There are also some other social input indicators such as investment in customer relationship management (Akdeniz, Gonzalez-Padron, & Calantone, 2010), qualitative control (Kuo & Lin, 2012), and investment in work safety (Ødegaard & Roos, 2014). As for the outputs, output yield, revenue and sales are three most popular indicators in economic output. The most frequently used environmental output indicators are all kinds of pollution emissions such as carbon monoxide emissions, carbon dioxide emissions, nitrogen oxide emissions, and SO_2 emission. The social output indicators include service and

[1] The input degree of a vertex means the number of edges pointing to this vertex, which represents the vertex paper is cited by how many other papers.

Table 5
Indicators used in corporate sustainability assessment.

	Input indicator	Output indicator
Economic	Assets, capital, materials and machinery, R&D cost, administrative expenses, marketing expense, operating cost, transportation cost, staff cost, technical risk, commercial risk	Output yield, revenue or net income, sales, profit, return on assets, value-added, market share, Tobin's q and market value, intangible assets
Environmental	Energy consumption, land use, investment in CO_2 abatement, investment for environment protection, carbon footprint, energy footprint, water footprint, waste generated, waste treatment cost, pesticide risk, erosion	Hydrocarbon emissions, carbon monoxide emissions, carbon dioxide emissions, nitrogen oxide emissions, SO_2 emission, pollution prevention and treatment, waste recycled, agri-environmental payments, environmental certification, estimated CO_2 saving, environmental costs savings initiatives, climate change, environmental management and innovation, environmental strength
Social	Cost of work safety, labor health, human labor, investment in customer relationship management, delivery punctuality and accuracy, supplier rejection rate, qualitative control	Quality, flexibility, service and customer satisfaction, human rights, delivery punctuality and accuracy, capacity and safety, community, diversity, social contribution, corporate transparency, cooperation

customer satisfaction (Kim et al., 2011), human rights (Lee & Saen, 2012), social contribution (Chen & Delmas, 2011) and so on.

Färe et al. (1996) is the first to use DEA methods to obtain corporate environmental performance by taking the weak disposability of bad outputs into account. Specifically, they decompose overall productive efficiency into input efficiency and environmental efficiency. Tyteca (1997) proposes to consider three different DEA models—undesirable output-oriented index model, both inputs and undesirable outputs oriented index model, and normalized undesirable output oriented index model, and uses them to measure the environmental performance of U.S. fossil fuel-fired electric utilities. A number of subsequent studies have used similar approaches in other industrial applications (e.g., Ball, Lovell, Nehring, & Somwaru, 1994; Piot-Lepeti & Vermersch, 1998; Sharma, Leung, Chen, & Peterson, 1999; Weber, 1996; Zhou, Chung, & Zhang, 2013; Zofio & Prieto, 2001). De Koeijer, Wossink, Struik, and Renkema (2002) first propose the concept of sustainability efficiency, and integrate DEA estimates of environmental and economic efficiency in a sustainability index. After the review article by Zhou et al. (2008b), more and more advanced DEA methods have been applied to address special problems in corporate sustainability assessment including dual-role factors model (Lee & Saen, 2012), directional distance functions (DDF) for different facets of eco-efficiency (Picazo-Tadeo, Beltrán-Esteve, & Gómez-Limón, 2012), Economic Input–Output Life Cycle Assessment (EIO-LCA) for assessing continuing impact of economic activities (Egilmez et al., 2013), Em+DEA method for energy analysis (Iribarren, Vázquez-Rowe, Rugani, & Benetto, 2014), and network DEA for studying the internal process of corporate production (Zhu, Wang, & Zhang, 2014). In the research stream of environmental efficiency evaluation, undesirable outputs are typically included in DEA models mostly as either inputs, some form of translated outputs or weakly disposable outputs. However, the efficiency findings from different studies can be hardly comparable because they are contingent upon the specific definition of undesirable outputs (Scheel, 2001). To overcome this problem, Asmild and Hougaard (2006) propose a two-step directional DEA approach to disaggregate undesirable nutrient surpluses into nutrient flows, which does not need to make the specific definition of undesirable outputs and makes the outputs (nutrient removal) desirable. Another way to avoid the problems associated with defining and dealing with undesirable outputs is proposed by Coelli et al. (2007). Specifically, they incorporate the materials balance concept into the production model and produce a new environmental efficiency measure that can be decomposed into technical and allocative components.

Another stream of research in the area focuses on how to improve corporate sustainability through technology innovation using different DEA models, such as non-radial approach (Sueyoshi & Goto, 2014a), radial and non-radial integrated approach (Sueyoshi & Wang, 2014), radial measurement with subcomponent measures (Sueyoshi & Goto, 2014b). Sueyoshi and Goto (2015a) also measure the scale efficiency and the influence of the small number ε for the first time. Afterwards, they extend the corporate sustainability research to the intertemporal dimension by using DEA Malmquist index (Sueyoshi & Goto, 2015b, c). They also propose some new DEA approaches to handle zero and negative values for both the radial and non-radial measurements (Sueyoshi & Goto, 2015c; Sueyoshi & Yuan, 2015b). Sueyoshi and Yuan (2016a) discuss the new use of DEA environmental assessment with multiplier restriction to measure Marginal Rate of Transformation (MRT) and Rate of Substitution (RS) among production factors. This research route is part of the key route of DEA application in sustainability as discussed before.

A third research theme emerged in this area is related to corporate social responsibility (CSR). CSR refers to a company's positive impact on society and the environment, through its operations, products or services and through its interaction with key stakeholders such as employees, customers, investors, communities and suppliers. Belu (2009) first proposes a cross-sectional DEA output-oriented model for analyzing the relationship between corporate economic and financial performance and social responsibility. Chen and Delmas (2011) utilize the DEA model for ordinal data (Cook & Zhu, 2006) to create a single CSP efficiency index and make a comparison between current aggregation approaches to justify the DEA approach's advantages. Chen and Delmas (2012) then develop a new eco-inefficiency frontier model that uses the additive inefficiency index and allow firms to select their own directions for improvement to reach the efficiency frontier. But the existing DEA papers for CSR are still relatively rare compared to the increasing attention to CSR in both business practices and academic research.

In summary, current DEA applications in corporate sustainability assessment mainly include three research topics: evaluate corporate eco-efficiency, improve corporate environmental efficiency, and measure corporate social performance. A wide range of DEA methods have been developed and applied into this research area from the classical DEA model, to hyperbolic efficiency measures, to models handling dual-role factors and cross-efficiency, DDF, LCA+DEA, Em+DEA, network DEA, multiplier restriction and the Malmquist index, etc. The incorporation of the materials balance concept into DEA research is also an important development.

5.1.2. Future directions

There are several directions for future DEA application in corporate sustainability. First, DEA methods such as network DEA and integrated DEA can be combined with other data analysis methods such as AHP, PCA, ANOVA, Sensitivity Analysis, econometrics and so on. The combination of DEA and other data analysis methods can provide a more accurate way for indicator selection, an objective evaluation of corporate sustainability and a proper explanation for corporate unsustainability. For example, network DEA could be further developed in corporate sustainability by considering the stage property of production process to reduce evaluation errors and find the deep-seated reasons for corporate unsustainability.

In addition, the problem associated with defining and dealing with undesirable outputs in DEA sustainability evaluation is getting more and more attention in the literature. Although two approaches have been proposed to mitigate such problems including the directional network DEA approach and the incorporation of the materials balance concept into the production model, future research should further develop these two methods as well as other more effective models for the handling of undesirable output problems.

Finally, the existing literature mainly focuses on the environmental aspect of sustainability, and only a few articles study the social aspect. Thus, more research is needed to apply DEA models in the CSR area from CSR modeling to empirical investigations on the relationship between CSR and corporate sustainability. Furthermore, a synthesized consideration of all the triple bottom lines of sustainability (*economic*, *environmental*, and *social*) is needed in future research on corporate sustainability assessment.

5.2. Sustainability composite indicators construction

5.2.1. Current status of the literature

A composite indicator (CI) is a mathematical aggregation of a set of individual indicators that measure multi-dimensional concepts but usually have no common units of measurement (Nardo et al., 2005). It has been widely accepted as a tool for performance monitoring, benchmarking, policy analysis and public communication in the sustainability field. DEA has been extensively applied to CI construction.

The use of DEA in CI construction can be divided into two groups. One group follows the tradition of DEA by first identifying inputs and outputs and then constructing an aggregated index using the common DEA procedure. The first paper in this group, Chung et al. (1997) introduce a directional distance function and use it as a component in a new productivity index – Malmquist–Luenberger productivity index that readily models joint production of goods and bads. Later, their index method is applied to a series of sustainability studies (e.g., He, Zhang, Lei, Fu, & Xu, 2013; Lin, Yang, & Chen, 2011). Since then, researchers have developed various DEA models to construct sustainability CIs. Callens and Tyteca (1999) build indicators based on the concepts of cost-benefit analysis and the principles of productive efficiency. By allowing for the assessment of business participation into sustainable development, they demonstrate that economic, social and environmental efficiency is a necessary (but not sufficient) step towards sustainability. Reinhard, Lovell, and Thijssen (2000) compare DEA and SFA methods for the calculation of efficiency. Tsolas and Manoliadis (2003) then apply DEA methods to establish a sustainability index including environmental impact for thermal electrical power production in Greece. Zhou and Ang (2008b) present several DEA-type linear programing models to measure economy-wide energy efficiency performance considering undesirable outputs. Zhang et al. (2008) envision the undesirable outputs as inputs and use a CCR DEA model to establish the index of industrial eco-efficiency. Their work includes the environmental impacts related to both resource use and pollution emissions. To better select the important input and output indicators, Azad and Ancev (2010) use DEA methods to compute the component distance functions in order to construct an environmental performance index (EPI) (Färe, Grosskopf, & Hernandez-Sancho, 2004). Pérez, Guerrero, González, Pérez, and Caballero (2013) combine Principal Component Analysis (PCA) and DEA to address some objections related to the aggregation procedure. Murty, Russell, and Levkoff (2012) first criticize the modeling of pollutants as inputs or weakly disposable outputs and propose a new model of pollution-generating technologies as an intersection of an intended-production technology of the firm and nature's residual-generation set, which they call *by-production technology*. They then use the intersection of two other types of distance function rather than the directional distance functions or hyperbolic distance functions, in the intended-production technology and a residual-generation technology to obtain the efficiency indices.

In this line of research, new DEA models have been proposed to better reflect the real situation, such as Slacks-based efficiency Measure (Choi et al., 2012), Multi-directional Efficiency Analysis (MEA) approach (Wang, Zhou, & Zhou, 2013), and Range-Adjusted Measure based DEA (RAM-DEA) models (Wang et al., 2013). Kumar et al. (2014) propose Green DEA (GDEA), which is built on an existing DEA model with weight restrictions, which provides a common framework for future research in terms of a green supplier selection strategy and other multi criteria decision making problems. Dong et al. (2015) evaluate a composite indicator that builds on a combination of non-negative PCA and common-weight DEA. In order to avoid "discriminating power problem" and "technical regress" occurred in previous DEA models, Li and Lin (2015a) establish a new environmental production possibility set by combining the super-efficiency and sequential DEA models, and construct the CI of energy efficiency performance using a meta-frontier framework with the improved directional distance function (DDF).

The other group of research in CI construction first transforms the sub-indicators into the same type of variables (benefit or cost type) and then aggregates them into a CI by DEA models. Zhou, Ang, and Poh (2007) first adopt this method to construct a CI for modeling the sustainable energy development of eighteen APEC economies in 2002. The proposed approach uses two sets of weights that are most and least favorable for each entity, thereby providing a more reasonable and encompassing CI. Similarly, Zhou et al. (2010) propose another DEA-like model considering the weighted product (WP) method instead of weighted additive one for data aggregation. Hatefi and Torabi (2010) modify the DEA-like model of Zhou's to introduce a common weight MCDA–DEA model to construct CIs. Blancard and Hoarau (2013) follow the same approach and apply the multiplicative optimization approach of Zhou et al. (2010) to construct CIs. Giambona and Vassallo (2014) aggregate CIs via a DEA-BoD (benefit-of-doubt) approach with weights determined endogenously by imposing proportion constraints. Wang (2015) extends existing approaches in MCDA–DEA field by establishing a generalized framework to construct a CI. He introduces the slacks-based CI combining with the Malmquist index for both static and dynamic analysis.

5.2.2. Future directions

In this research cluster, the applications of DEA mainly focus on the macro level by constructing the CI for regions or industries. Our review reveals two key research routes in the CI construction: one is identifying inputs and outputs, and the other is firstly transforming all the sub-indicators into the same type of variables (benefit or cost type).

In future study, DEA methods can be used to directly construct the CIs, or to indirectly compute the key variables of a CI, like the component distance function. Since the DEA methods in CI construction has been well established, the future research should pay more attention to the combination of DEA methods with other statistics approaches such as PCA and AHP in CI construction. Weight setting is another area that requires most attention, especially when transforming the sub-indicators with either weight restrictions subjectively or determined endogenously. What is also notable is that the material-balance condition is a valuable direction for by-production technology in building sustainability composite indicators. In addition, current CIs mainly contain economic and environmental indicators but have limited social indicators. Thus, future CI construction should pay more attention to social indicators so that it could better reflect the social sustainability performance.

5.3. Sustainability performance analysis

5.3.1. Current status of the literature

Research in sustainability performance analysis mainly focuses on evaluating the relationships between different aspects of sustainability such as economic sustainability and environmental sustainability and identifying the impact factors of sustainability typically through the two-stage approach. The leading paper on the development trajectory, Zheng, Liu, and Bigsten (1998) is the first to use the two-stage approach (DEA methods in the first step and Tobit regression second) to analyze determinants of technical efficiency. Following them, Sarkis and Corderio (2001) use the two-stage approach to test the corporate environmentalism-financial performance linkage. After these pioneer works, research is diverged into two streams according to the methodologies used. One stream is mainly based on the two-stage approach, including static and dynamic analysis. Ylvinger (2003) points out the necessity of unified-assessment in sustainability performance evaluation including economic, environmental and social aspects. He then uses seven always-solvable DEA models in one-time period to measure product performance and policy performance to identify their impact-factors. This line of research is extended by Sarkis (2006) to a time series context using DEA models in the first stage and non-parametric statistics (the Mann–Whitney U-test) in the second to investigate the relationship between environmental performance and adoption of environmental and risk management practices. His work invites a series of subsequent two-stage studies with the integration of various DEA models and other methods such as variance analysis (Lopez-Cabrales, Valle, & Herrero, 2006), simulation models (Speelman et al., 2009), correlation analysis (Nuti, Daraio, Speroni, & Vainieri, 2011), Tobit regressions (Shieh, 2012), and sensitivity analysis (West, 2015).

Graham (2009) is the first to use an environmentally sensitive DEA Malmquist productivity index to see how environmental services influence measured productivity in the long run. The ability to incorporate environmental impacts without price data into a Malmquist productivity index makes the index attractive for the present study. Ødegaard and Roos (2014) combine Malmquist index and bootstrap DEA to analyze the contribution of labor quality attributes toward firm productivity. Then Arabi, Munisamy, Emrouznejad, and Shadman (2014) introduces a new slacks-based model for Malmquist–Luenberger (ML) Index incorporating bad outputs. Recently, the equality of the efficiency score distributions is also getting scholar's attention. For example, Kenjegalieva, Simper, Weyman-Jones, and Zelenyuk (2009) utilize the bootstrap-based Simar–Zelenyuk-adapted-Li test to estimate and statistically compare the distributions of estimated efficiency scores.

The other research stream mainly includes the papers using the input–output approach in a life-cycle context as a complement to DEA methods in sustainability analysis. Munksgaard et al. (2005) introduce the input–output approach operating in a life-cycle context into establishing general measures of environmental quality as a complement to DEA methods. EIO-LCA is employed to quantify the environmental impacts associated with the economic activities (Egilmez & Park, 2014). Egilmez et al. (2014) apply the above EIO-LCA and DEA methods to supply chain sustainability analysis and measure the sensitivity of environmental impact indicators using a sensitivity analysis.

In addition to these two main research streams discussed above, some other methods have been applied to find out the impact factors of sustainability. For example, Färe, Grosskopf, and Pasurka (2007) investigate the association between pollution abatement activities and traditional productivity by comparing productivity when bad output production is regulated vs. not regulated. Wang and Wei (2016) develop a new decomposition method to examine the contributions of each individual energy input and undesirable output toward productivity change. Other methodological development in this area include two-stage environmental network DEA model (Li, Chen, Liang, & Xie, 2012), variable coefficient test and fuzzy theory (Song, Tao, & Wang, 2015), counterfactual experiment (Shi, Yan, Shi, & Ke, 2015), strategy map (Sánchez, 2015) and three-stage DEA model (Li & Lin, 2016).

5.3.2. Future directions

Currently the two main methodologies used for sustainability analysis are the two-stage approach, and integrated methodology of DEA and EIO-LCA. Although the two-stage research stream has evolved from static analysis to intertemporal analysis, most of the DEA models still treat the production process as a "black-box" when analyzing the impact factors of the overall efficiency. However, a production process could have multiple stages, and therefore evaluating the efficiency of every single stage separately would be necessary and useful to diagnose and improve the overall efficiency of production activities. So in future research, more network DEA models should be used in combination with the two-stage contextual factor analysis. What is also notable is that recently some papers have used the Simar–Zelenyuk-adapted-Li test (Simar & Zelenyuk, 2006) to test the differences among distributions of performance scores. This non-parametric test is particularly suitable for DEA analyses and could be applied to future two-stage analyses on the determinants of sustainability.

On the other hand, the research stream with integration of DEA and EIO-LCA has not been extended to the dynamic dimension yet. Environmental impacts of economic activities often have time lag and thus cross-sectional data usually cannot accurately test economic activities' impacts over time. In the future, longitudinal data should be collected and employed in the EIO-LCA with dynamic DEA models to assess the dynamic impact of environmental factors. In addition, the current input output life cycle assessment mainly focuses on the economic activities' impacts on environment rather than their social influences. To investigate the whole picture of sustainability issues, more advanced DEA models are needed to incorporate social aspects in the sustainability strategic decision-making processes.

5.4. Regional sustainable development assessment

5.4.1. Current status of the literature

DEA is frequently used to evaluate the sustainability of regional development in support of the formulation of regional sustainable development policy. Table 6 lists the indicators usually used by DEA for region DMUs evaluation.

As shown in Table 6, the most popular economic input is capital including both material and financial capital. Energy consumption is the most used environmental input. In some cases, CO_2 emissions are also used as environmental input for regional sustainability measurement (Zhou et al., 2007). Labor and population are the commonly used social input indicators along with other social input indicators such as Gini indicator (Bosetti & Buchner, 2009), human capital and degrees of market openness (Lei et al., 2013). In output dimension, the economic and environmental indicators for a region are similar to those at the corporate level including GDP, CO_2 emission, etc. The adopted social outputs for a region include employment, crude birth rate, number of hospital beds and doctors (Munda & Saisana, 2011), city satisfaction scores (Akyol & Koster, 2013), Gini indicator (Zhang, Kong, & Choi, 2014).

Our review reveals two different streams in the literature to apply DEA models to the regional sustainable development assessment. One stream is about static sustainability research

Table 6
Indicators used in regional sustainability assessment.

	Input indicator	Output indicator
Economic	Capital (material and financial), consumption expense, budget, transportation costs, R&D expenditure, patent applications	GDP, gross regional product (GRP), value added of industries, total revenue, output yield, ANS (adjusted net saving)
Environmental	Energy consumption, CO_2 emissions, pollution investment, increase in temperature, land use, precipitation average, total local (PM_{10}, NO_x), soil loss and nitrogen loss	Sulfur dioxide emission, PM_{10}, NO_2, soot, industrial dust, solid waste, CO_2 emission, investment in waste water collection
Social	Human labor, population, inequity indicator, Gini indicator, human capital, unemployment, degrees of market openness	Total number of visitors, employment, crude birth rate, city satisfaction scores, Gini indicator, number of hospital beds and doctors

based on sectional data. This line of research begins with Lu and Lo (2007a) who create a cross-efficiency measure (CEM) based on Seiford and Zhu's (2002) data translation approach to deals with undesirable outputs and false positive index (FPI) and then to further analyze the regional development of China. In their next paper in 2007, they sequentially integrate CEM and cluster analysis to construct a benchmark-learning roadmap for inefficient regions. Akyol and Koster (2013) extend these CEM models by making the trade-offs between different objectives in economic, environmental and social development. To mitigate the issue of incomparability of different DEA models, Bian and Yang (2010) extend Shannon-DEA procedure (Soleimani-damaneh & Zarepisheh, 2009) by integrating different resource and environment performance models when measuring DMUs' performance. Munda and Saisana (2011) present a methodological framework based on a non-linear/non-compensatory multi-criteria approach (Munda, 2005; Munda & Nardo, 2009) and DEA, and combine with sensitivity analysis for assessing regional sustainability. Houshyar, Azadi, Almassi, Davoodi, and Witlox (2012) use a combination of fuzzy logic and DEA models to evaluate the energy use sustainability for better estimation. Chang, Zhang, Danao, and Zhang (2013) propose a non-radial DEA model with the slacks-based measure (SBM) to analyze the environmental efficiency.

The other research stream mainly focuses on intertemporal sustainability assessment. Many researchers have applied traditional DEA models and Malmquist index to analyze regional dynamic relative macroeconomic performance, energy efficiency and water efficiency in China (e.g., Chen, Song, & Xu, 2015; Guo et al., 2011; Hu & Wang, 2006; Hu et al, 2006; Hu et al., 2005; Li & Hu, 2012; Zhou et al., 2010). In order to use panel data to estimate the production frontier, Zhou and Ang (2008a) present a production-theoretical decomposition analysis (PDA) approach based on the Shephard input distance function and the environmental DEA technology concepts. Different from the traditional DEA models, Lee, Hu, and Kao (2011) create an input-saving index by comparing the actual energy inputs to target energy inputs, and compute the energy-saving targets for 27 regions in China during the period 2000–2003. DEA window analysis technique and corresponding rank sum test are also combined with energy and emission performance evaluation models in order to give a dynamic evaluation of regional sustainability (Wang et al., 2013; Wang, Wei, & Zhang, 2012). To deal with the modeling of the undesirable outputs, Wang and Wei (2014) introduce a hybrid model to evaluate the regional energy and emissions efficiency. Their model ensures the economically meaningful jointness of good and bad outputs while constraining shadow prices of bad outputs to their expected sign as in Leleu (2013). Piña and Martínez (2016) use DEA models to measure urban sustainability, incorporating indicators related to social performance for the first time.

Recently, some new DEA models have been applied in regional sustainable development assessment, such as non-radial directional distance function (Wang et al., 2013), sequential generalized directional distance approach (Zhang et al., 2014), non-oriented DDF model (Chang, 2015), driving forces-pressure-state-impact-policy (DPSIP) model (Kuo & Tsou, 2015), and bounded adjusted measure (BAM) (Rashidi & Saen, 2015). These new DEA models can be applied in both static and dynamic assessment for regional sustainability. The DEA methods are used in combination with other methods in regional sustainability evaluation, for example, Shannon's entropy index (Storto, 2016).

5.4.2. Future directions

Many DEA models have found their applications in regional sustainability development assessment from static analysis to dynamic analysis in combination with, many other approaches such as sensitivity analysis, fuzzy logic, etc. Although the unified assessment with integration of multi-DEA methods and other methods is becoming a trend in regional sustainable development, there are still some limitations to be solved. First, the current regional research does not consider difference industrial structures among different regions. It may not be accurate to treat all regions as homogeneous DMUs. In future research, we can try to use non-homogeneous DEA models to evaluate regional sustainability. Second, the existing literature mostly considers the region as a "black-box" and future research could use network DEA models to break the box for further study. Third, as to the research content, the previous regional studies are mainly based on issues related to environmental sustainability such as energy use. Social sustainability so far has been under investigated and therefore future studies should consider using indicators of social welfare.

6. Conclusion

Our study fills a gap in the DEA literature by conducting a systematic survey on DEA applications in sustainability. This survey covers DEA papers listed in the Web of Science database from 1996 through March 2016. With the assistance of three citation analysis methods—citation chronological graph, main path method and Kamada–Kawai algorithm, we identify citation networks, significant paths, important papers, and research clusters in DEA application in sustainability. The review results show that the current key route of DEA application in sustainability focuses on the eco-efficiency measurement that maximize economic outputs while minimize negative environmental influence. One of the key challenges in the DEA sustainability research is how to deal with undesirable or bad outputs. Our review reveals three major approaches: the weak disposability approach, the natural and managerial disposability, and the materials balance approach. Four major research clusters are identified: corporate sustainability assessment, sustainability composite indicators construction, sustainability performance analysis and regional sustainability development assessment.

Five interesting phenomena are observed from the development trajectories analysis on the four focal clusters. First, there is a pattern of technology-adoption process by DEA researchers. Early adopters start with the classical DEA models and cautiously suggest the usefulness of the methodology. After DEA is accepted in the field, researchers tend to adopt the newly developed approaches and models once they are available. Second, a pattern of research perspective development can be found. The DEA application in sustainability usually begins with static measurement, and then extends to dynamic measurement. As to the evaluated objectives, previous research often starts with external evaluation treating DMUs as black-box, and then turns to internal research considering different internal structures and production processes. Third, more and more sustainability evaluation studies start to make comprehensive assessments on objectives, from traditional economic assessment to early environmental sustainability, and then to recent social sustainability. Fourth, there is a significant trend emphasizing on the combination of DEA with other analytical methods such as AHP, game theory, LCA, and regression analysis, etc. for more accurate and reliable assessment results. Fifth, the two-stage process model, a simple form of the network DEA model, has drawn much attention lately across applications. The typical two-stage process model breaks the limitations of traditional black-box model with a subdivision production process and can evaluate the sustainability of different process stages or supply chain aspects.

Several gaps in the literature are also revealed. First, the extant DEA application research on sustainability in OR/MS still mainly focuses on the economic and environmental measures (emissions, remanufacturing, waste reduction, etc.) while models that examine the social measures are lacking in the literature. The lack of social measures may be due to the availability of micro and/or macro data related to social indicators (e.g., social contribution, service and customer satisfaction) and methodological challenges to incorporate social measures in DEA models (e.g., how to deal with the relationship between social indicators and economic/environmental indicators). New DEA methods should be developed to incorporate the interaction of social, economic and environmental measures, and to well character the complexity of social network, which means when evaluating the DMUs' social sustainability, we should consider their social network relationship and the relationship with the external environment. Second, there are three dimensions of the synthesis research of sustainability: content, process and context. The extant papers mainly focus on the content, but the analysis on the process and context of sustainability is under-investigated, for example, different industrial structures when evaluating regional sustainability and self-sufficiency rates in energy supply of nations. Third, the current research on sustainability evaluation does not contain the institution dimension that could have a significant impact on sustainability. Future research could synthesize the institutional perspective with the triple bottom line of sustainability. In addition to the gaps mentioned above, other methodological challenges are still waiting to be explored such as the time lag between inputs and output, the occurrence of multiple solutions, future cost and energy uncertainty and so on.

The interpretation of these results should nevertheless take the following limitations into consideration. First, the data are collected from the WOS database and do not include all DEA papers published in journals that are not included in the WOS. Second, albeit much effort has been made to select correct DEA sustainability papers, we may still miss some DEA papers, we believe that these papers would be a very small percentage of the total papers and do not change the major analysis results. Third, although highly cited publications to some extent represent the core content and evolution of the research, but when compared with the whole number of articles, the limited amount of data can cause inevitable one-sidedness, which is also a limitation and drawback of chronological diagram research. Fourth, the results of the local main path analysis are subject to citation noise, a general limitation of the citation analysis. Citation noise occurs when 'remote' citation occurs occasionally when a paper cites others, not because of a close connection with the main subject, but merely because of a connection in a broad sense such as the same application area, the same general method, or even just because of applying DEA methodology (Liu et al., 2013). The tail portions of the main path are especially sensitive to these noises as the number of citation count becomes fewer there. Thus, it should be cautious when interpreting the results close to the tail. Finally, there has been a debate on whether the DEA-based approach is applicable to sustainability analysis in the literature. Some scholars (e.g., Callens and Tyteca, 1998; Huppes & Ishikawa, 2005) argue that efficiency in DEA models is a relative concept that may not be suitable to evaluate sustainability performance, an absolute concept that has to do with absolute magnitudes concerning the absorption capacity of ecosystems An efficient DMU does not imply to be sustainable as efficiency is only a necessary condition (or intermediate step) for sustainability. But in our opinion, first of all, it is debatable that sustainability performance only is an absolute concept. An assessment on relative sustainability levels could provide a benchmark system that help companies find the most cost-effective way to achieve a reduction in environmental degradation and policymakers adopt policies aimed at achieving improvements rather than simply restrict economic activities (Gómez-Limón, Picazo-Tadeo, & Reig-Martínez, 2012; Kuosmanen & Kortelainen, 2005). For those reasons, we believe DEA is still a valuable tool for sustainability performance evaluation.

In conclusion, sustainability is an area that is gaining interest and DEA has been proved be an appropriate evaluation method for sustainability in the literatures. The development on DEA methodologies and applications in sustainability should continue to flourish. We hope that this review can be a useful and inspirational source for further DEA research on sustainability.

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