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Life cycle-based environmental performance indicator for the coal-to-energy supply chain: A Chinese case application

Pezhman Ghadimi[a,b], Chao Wang[c,d,*], Amir Hossein Azadnia[e], Ming K Lim[f,g], John W. Sutherland[h]

[a] School of Mechanical and Materials Engineering, University College Dublin, Dublin, Ireland
[b] Beijing Dublin International College, Beijing University of Technology, Beijing, 100124, China
[c] Research Base of Beijing Modern Manufacturing Development, College of Economics and Management, Beijing University of Technology, Beijing, China
[d] Center for Polymer Studies and Department of Physics, Boston University, Boston, MA, USA
[e] Department of Industrial Engineering, Ayatollah Amoli Branch, Islamic Azad University, Amol, Iran
[f] College of Mechanical Engineering, Chongqing University, Chongqing, China
[g] Centre for Business in Society, Coventry University, Coventry, UK
[h] Environmental and Ecological Engineering, Purdue University, West Lafayette, IN, USA

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ABSTRACT

Coal consumption and energy production (CCEP) has received increasing attention since coal-fired power plants play a dominant role in the power sector worldwide. In China, coal is expected to retain its primary energy position over the next few decades. However, a large share of CO_2 emissions and other environmental hazards, such as SO_2 and NO_x, are attributed to coal consumption. Therefore, understanding the environmental implications of the life cycle of coal from its production in coal mines to its consumption at coal-fired power plants is an essential task. Evaluation of such environmental burdens can be conducted using the life cycle assessment (LCA) tool. The main issues with the traditional LCA results are the lack of a numerical magnitude associated with the performance level of the obtained environmental burden values and the inherent uncertainty associated with the output results. This issue was addressed in this research by integrating the traditional LCA methodology with a weighted fuzzy inference system model, which is applied to a Chinese coal-to-energy supply chain system to demonstrate its applicability and effectiveness. Regarding the coal-to-energy supply chain under investigation, the CCEP environmental performance has been determined as "medium performance", with an indicator score of 39.15%. Accordingly, the decision makers suggested additional scenarios (redesign, equipment replacement, etc.) to improve the performance. A scenario-based analysis was designed to identify alternative paths to mitigate the environmental impact of the coal-to-energy supply chain. Finally, limitations and possible future work are discussed, and the conclusions are presented.

1. Introduction

The use of fossil fuels has been linked to climate change and environmental vulnerability. The World Wildlife Fund (WWF) has estimated that the current production and consumption patterns in the United States (US), if replicated across the globe, would require the equivalent resources of three Earths (WWF, 2016). Scientific communities realize that the pursuit of greener production and consumption practices is necessary (Govindan, 2018; Tseng et al., 2018) and are devoting efforts to promote and implement green practices in production and consumption in various industries (Wang et al., 2018).

Globally, coal consumption accounts for approximately 30% of primary energy requirements. This amount of coal generates approximately 40% of the world's electricity needs (He et al., 2017; Su et al., 2017) and is expected to retain its primary energy position over the next two decades (Şengül et al., 2016). Moreover, industrial countries are likely to rely more on their own produced energy sources such as coal. These types of strategies are undertaken mainly because of the volatility of oil prices of the major oil/gas producing regions such as the Middle East (Apergis and Payne, 2010). However, this reliance increases the amount of environmental hazards generated in such industrial countries. Such concerns over the past decades have resulted in numerous studies to estimate the environmental impact of coal using a life cycle analysis approach (Cui et al., 2012; Ding et al., 2017; Vujić

* Corresponding author at: College of Economics and Management, Beijing University of Technology, Chaoyang District, Beijing, 100124, China.
E-mail address: chaowanghn@vip.163.com (C. Wang).

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et al., 2012; Zhou et al., 2019), which is a method also recommended in the U.N. sustainable development goals (SDGs) (United Nations, 2015).

In spite of the foregoing comments, valuable environmental impact assessment results should enable decision makers (DMs) inside an organization to understand, comprehend and compare them with other environmental indicators (Schneider et al., 2011). This highlights the importance of an easily understandable environmental performance indicator for coal consumption and energy production (CCEP). To our knowledge, such an environmental performance indicator has yet to be developed for CCEP. Such an indicator would act as a reliable tool for increasing the understanding and facilitating the interpretation of life cycle assessment (LCA) results by industrial practitioners. This lack forms the motivation for this paper, which will propose an integrated LCA and fuzzy inference system (FIS) framework to produce an environmental performance indicator. The developed indicator will serve as a practical way to evaluate the effects of changes to the CCEP processes and can enhance corporate-level decision-making. To illustrate the utility of the indicator, a Chinese coal-to-energy supply chain (SC) will be evaluated.

This article is organized as follows. A comprehensive review of relevant literature is presented in Section 2, which summarizes work related to LCA applied to CCEP and LCA combined with FIS. The theoretical underpinning of this study and the developed CCEP environmental performance indicator framework are detailed in Section 3. Moreover, Section 4 presents the application results based on a coal-to-energy SC case study. An alternative scenario-based analysis is reported in Section 5. The theoretical and managerial insights related to this research work are discussed in Section 6. Finally, some remarks, directions for future research, and conclusions are offered in Section 7.

2. Literature review

In this section, LCA applied to coal consumption and energy production and LCA combined with fuzzy inference systems are reviewed. In addition, identified research contributions and gaps are highlighted.

2.1. LCA applied to coal consumption and energy production

Effective evaluation of the environmental burdens can be conducted using the LCA tool (Hellweg and Milà i Canals, 2014). A vast array of literature has studied the influences of coal production or coal consumption on the environment using LCA (Aguirre-Villegas and Benson, 2017; Awuah-Offei and Adekpedjou, 2011; Şengül et al., 2016; Wang and Mu, 2014; Yu et al., 2014). The scholarly works related to the coal supply-side reported the environmental impact of coal mining operations and emphasized reducing the environmental issues at the coal extraction/production stage (Bian et al., 2010; Burchart-Korol et al., 2016; Cheng et al., 2011; Pell et al., 2019; Si et al., 2010). The works related to the coal demand-side analyzed the environmental impact of coal consumption, such as its use in chemical plants, power plants, steel mills, and cement factories (Guo et al., 2018; Hossain et al., 2017; Luo et al., 2017; Morais et al., 2011; Singh et al., 2015; Yang et al., 2017). Following the work by Spath et al. (1999) focusing on coal-fired power plants (CFPPs), many scholars have investigated the environmental impacts of generating electricity using coal (Babbitt and Lindner, 2005; Rakotoson and Praene, 2017; Whitaker et al., 2012).

Influenced by Goal #12 of the U.N. SDGs, several studies have combined coal production (extraction) and coal consumption (e.g., energy production), which fall into the realm of integrated assessment studies. These relatively comprehensive studies analyzed the environmental impacts of the entire coal life cycle. Wang and Mu (2014) calculated the amount of waste gas emissions in a Chinese coal-to-energy SC. Yu et al. (2014) and Xu (2013) estimated China's coal-to-energy SC carbon emissions ranging from 875 $g/kW\,h^{-1}$ to 990.72 $g/kW\,h^{-1}$. Considering a power plant in Turkey, Şengül et al. (2016) performed lignite life cycle assessment considering the entire SC from the extraction point to the delivery point. In an LCA work conducted by Aguirre-Villegas and Benson (2017), various stages of an Indonesian coal SC including coal mining and transport to various market segments were analyzed with regard to their environmental impacts. The environmental burdens that are obtained as a result of the traditional LCA methodologies applied in these reviewed studies cannot be regarded as informative indicator scores since they do not provide a means for practical decision-making in terms of performance (either negative or positive) of an analyzed CCEP system. This lack of informative indicator scores makes it difficult for industrial practitioners and academics to make sense of the environmental burdens (results of a traditional LCA study) according to the obtained values for each environmental category.

2.2. LCA combined with fuzzy inference system

The main issue with traditional LCA results is the lack of numerical magnitude of the performance level regarding the obtained environmental burden values together with the inherent uncertainty associated with output results (Awuah-Offei and Adekpedjou, 2011; Wang and Mu, 2014). As discussed by Fitzgerald et al. (2012), FIS combined with LCA provides a promising future research direction. A fuzzy inference system utilizes fuzzy set theory to map a set of real values to values from 0 to 1. In other words, it has the capability to facilitate the stakeholders' decision-making process by providing a scaled environmental effect and addressing the uncertainty involved in the environmental burden results.

Within this context, few authors have examined the application of fuzzy set theory in conjunction with LCA methodology in various research disciplines (Afrinaldi and Zhang, 2014; Agarski et al., 2016; Benetto et al., 2008; Bovea and Wang, 2003; Egilmez et al., 2016; González et al., 2002; Güereca et al., 2007; Khoshnevisan et al., 2014; Liu, et al., 2012; Liu et al., 2012b; Mascle and Zhao, 2008; Memon et al., 2007; Weckenmann and Schwan, 2001). Table 1 highlights the application of fuzzy set theory combined with LCA by describing the developed approach considering the LCA boundaries and the application domain, i.e., product, process, or SC.

Based on Table 1, the incorporation of fuzzy set theory in LCA has been considered from various aspects, boundaries of analysis, and application perspectives. Fuzzy set theory has often been applied to capturing the input data uncertainty of the life cycle inventory stage of the LCA methodology, combined with multiple-criteria decision-making (MCDM) tools to enhance LCA results and used to develop an enhanced normalization step in LCA. It is also found that almost all the applications are focused on a single/group of product(s) or process(es). Accordingly, none of the reviewed research focused on considering the entire SC as the scope of their analysis. Furthermore, there are no applications that considered a coal-to-energy SC that covered both coal consumption and energy production as their case study. The current research work distinguishes itself from other research activities in the field and aims to fill the identified gaps in the literature by proposing a CCEP environmental performance indicator that integrates a weighted FIS model with an LCA methodology to enhance the results obtained via a traditional LCA application.

3. Material and methods

In this section, the theoretical underpinning and choice of tools utilized in the proposed framework are discussed in more detail.

3.1. Research design

The theoretical underpinning of this study is a weighted FIS model that combines the obtained LCIA results forming an integrated indicator framework for CCEP environmental performance measurement. It enhances the normalization process of the sub-category impact scores by

Table 1
LCA combined with fuzzy set theory.

Authors	Developed methodology	LCA boundary	Product/Process/SC
Weckenmann and Schwan (2001)	Utilized fuzzy set theory to improve the quality of LCA output results by removing the uncertainty and imprecision of input data	Cradle-to-gate	Wave soldering process for a printed circuit board
González et al. (2002)	Developed a simplified method by combining a fuzzy logic approach with LCA to carry out the assessment for small and medium-sized enterprises (SMEs)	Cradle-to-gate	Pre-manufacture stage for lamp production in an SME
Bovea and Wang (2003)	Utilized LCA combined with fuzzy set theory-based Quality Function Deployment (QFD) to evaluate the imprecision of customer preferences	Cradle-to-grave	Office table product
Güereca et al. (2007)	Developed a valuation methodology based on LCA combined with fuzzy set theory to obtain an order preference indicator of various bio-waste management scenarios	Cradle-to-grave	Bio-waste management processes
Benetto et al. (2008)	Combined normalized life cycle impact assessment (LCIA) results with a fuzzy multicriteria analysis method called NAIADE to rank various electricity production scenarios.	Cradle-to-grave	Coal-based electricity production processes
Liu et al. (2012)	Combined LCA with fuzzy logic to assess the emission- and nonemission-related environmental aspects to obtain severities ratios of these aspects.	Recycling stage	Construction waste recycling processes
Khoshnevisan et al. (2014)	Utilized adaptive neuro-fuzzy inference system (ANFIS) combined with LCA methodology to predict the environmental indices of crop production	Cradle-to-gate	Agri-food products
Afrinaldi and Zhang (2014)	Developed a normalization and aggregation approach based on FIS for the LCA methodology.	Cradle-to-gate	Automotive engine
Egilmez et al. (2016)	Combined fuzzy data envelopment analysis with LCA to remove uncertainty in life cycle inventory data.	Not provided	US food manufacturing sectors
Agarski et al. (2016)	Utilized FIS for obtaining the weighting factors of impact categories in LCA	Recycling stage	Waste treatment processes

utilizing target ranges for each environmental sub-category. In other words, although the traditional LCA approach provides a normalized environmental burden value for a process or product, this causes difficulties for DMs in understanding the numerical level of the environmental performance of such process or product. The developed combined LCA-FIS approach addresses such issues by providing a performance indicator framework that can be utilized to construct scenarios, make proper improvement decisions, and appropriately measure the environmental performance of these improvement scenarios. Furthermore, the developed FIS model contains a proposed heuristic based on a fuzzy analytic hierarchy process (FAHP) to consider the weights of the environmental sub-categories according to their importance. It is demonstrated that the integrated LCA-FIS evaluation with weighted environmental sub-categories makes the proposed method more accurate compared with a traditional FIS model. This enhanced accuracy mainly derives from the inclusion of expert knowledge related to the FAHP importance-weighting process.

3.2. CCEP environmental performance indicator framework

The proposed framework is formulated based on the integration of an LCA methodology with a developed FIS model, which is applied to a Chinese coal-to-energy SC system as a real-world application to demonstrate its effectiveness and applicability. The developed framework is depicted in Fig. 1. The framework encompasses two phases with the first phase commencing with defining the analysis objectives and scope. The second step of LCA deals with establishing a life cycle inventory (LCI) for the identified main SC processes. This is followed by the characterization process to produce an aggregated effect score with respect to the identified environmental sub-categories. In LCA, a product or process environmental impact is calculated based on the aggregation of all individual impacts related to various sub-categories. In this framework, the identified environmental sub-categories are classified into two main performance categories, i.e., regional and global environmental performance. The raw impact assessment results of the LCA are utilized as inputs for the proposed weighted FIS model, which enhances the interpretation step of the LCA methodology.

The traditional LCA encompasses the normalization and weighting steps. This results in a normalized environmental burden value. However, there are some deficiencies associated with this result. These deficiencies are the lack of a numerical magnitude of the environmental performance level and existence of uncertainty in the final environmental burden. In other words, the DMs inside a typical company or system where the LCA is implemented would face difficulties in understanding the relative performance of the analyzed products or processes within their system. Moreover, the uncertainty challenges involved in the outputs of a traditional LCA need to be overcome using a rigorous uncertainty analysis approach. These important criticisms of the traditional LCA approach were also highlighted and discussed by Awuah-Offei and Adekpedjou (2011) with specific reference to the mining industry, and these criticisms are also addressed in the application of the current research.

Accordingly, in the second phase of the framework, an FIS model is designed using Mamdani's inference rule (Mamdani, 1974). This model can address the discussed deficiencies involved with the traditional LCA results. After obtaining the input data in Phase 1 (raw impact assessment values), the FIS evaluation of the input variables is done in five stages.

- Sub-category importance weighting: Before implementing the fuzzy evaluation mechanism, Chang (1996)'s FAHP model is utilized to weight the sub-categories involved in the main categories for global and regional environmental performance based on their importance. Owing to limitations of space, readers are encouraged to review the FAHP mathematical formulations in Ghadimi et al. (2012). The obtained weights are then utilized in the fuzzy rule base construction of the fuzzy evaluation mechanism discussed below.
- Fuzzification: Various grades of membership functions (MFs) are assigned to the input data obtained from the life cycle impact assessment. For each of the impact sub-categories, which are the actual input variables, a minimum and maximum possible value are defined as a target range. The formulation of each related MF to the environmental sub-categories is done based on the defined target ranges. It is worth noting that devising improper target ranges can lead to subjective outputs. Therefore, it is recommended that these scales be defined based on various available sources, such as a DM's opinion or the environmental regulations and standards of a region or country. The developed FIS model in the proposed framework encompasses three types of triangular MFs corresponding to each input variable. These MFs are constructed based on the defined target scales: low (L), medium (M), and high (H).
- Weighted knowledge base (rule base): After constructing the MFs for each input variable (the environmental sub-categories), a knowledge base that mediates the internal behaviors of each of these MFs is defined. This knowledge base consists of several IF_THEN fuzzy rules. Eq. (1) provides the formula for calculating the number of

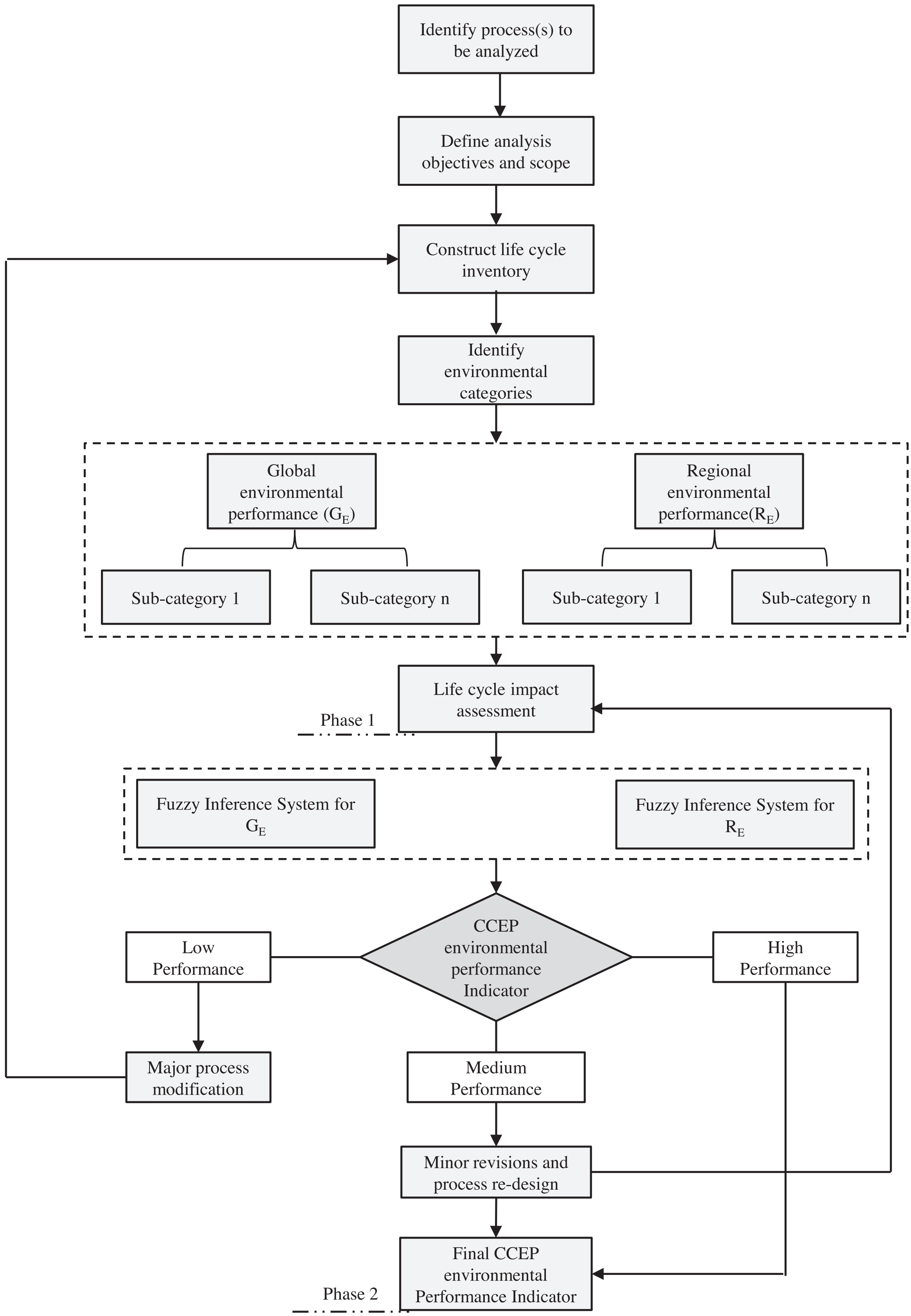

Fig. 1. CCEP environmental performance indicator framework.

these fuzzy rules related to each environmental main category (Cornelissen et al., 2001).

$$R = n^v \tag{1}$$

where

R - Number of potential rules for each environmental main category.

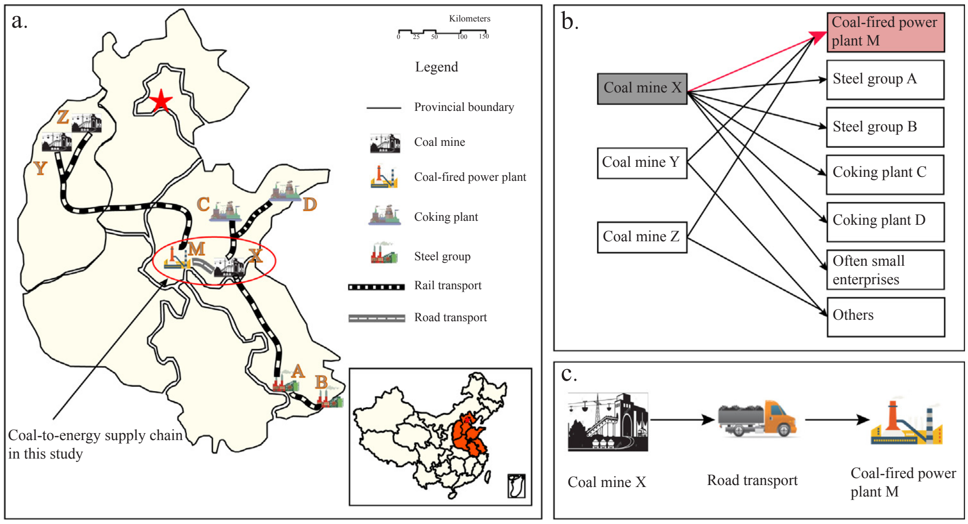

Fig. 2. A Chinese coal-to-energy SC including coal mining operations, road transport, and the coal combustion process.

n - Number of MF types for each environmental sub-category.

v - Number of sub-categories (input variables) related to each environmental main category

As the weights of the sub-categories (input variables) are different, these importance weights should be considered in the FIS structure as well. However, the traditional FIS is unable to deal with this issue; see Ghadimi et al. (2012). Hence, this research work presents the following new heuristic method to resolve the abovementioned issue:

Heuristic ranges for defining fuzzy rules

a) IF $\sum_{i=1}^{m} W_i A_i = 1$ THEN environmental performance is High.
b) IF $1 < \sum_{i=1}^{m} W_i A_i \leq 1.66$ THEN environmental performance is Medium to High.
c) IF $1.66 < \sum_{i=1}^{m} W_i A_i \leq 2.33$ THEN environmental performance is Medium.
d) IF $2.33 < \sum_{i=1}^{m} W_i A_i < 3$ THEN environmental performance is Low to Medium.
e) IF $\sum_{i=1}^{m} W_i A_i = 3$ THEN environmental performance is Low.

where

W_i - the importance weight of the i^{th} sub-category associated with the regional and global environmental main categories

A_i - the score given to each associated MF to the i^{th} sub-category

Accordingly, scores 1, 2, and 3 are set for the corresponding scores for the low, medium and high MFs, respectively. The weighted sub-categories are aggregated within the IF statements. This results in a THEN statement to each corresponding main category, which are the regional and global environmental performances.

- Fuzzy assessment: The aggregation and implication processes of the developed fuzzy inference model are performed within this step. The implication process encompasses the fuzzy conclusion related to each of defined fuzzy rules. This is done using known fuzzy operators i.e., AND, OR, and NOT. These operators are utilized to connect various components of a fuzzy rule and form the implication process output. In the next part, these output conclusions are aggregated with each other, and a single fuzzy set is constructed. The inputs to the aggregation process are characterized based on the implication process output functions. Finally, the output of the aggregation process is utilized in the defuzzification step.
- Defuzzification: In this step, five output MFs are devised that transfer the output of the previous step (fuzzy assessment) to a scale between 0 and 1. These output MFs are named low (L), low-to-medium (LM), medium (M), medium-to-high (MH), and high (H). The output of the defuzzification step provides a numeric crisp value that acts as a score for the environmental performance of any evaluated system (product, process or SC) with regards to the evaluated main category.

After obtaining each of the main category scores, the CCEP environmental indicator score can be calculated. The importance weightings for both regional and global environmental performance main categories are set to be equal in this analysis, which is put forward by the DMs inside a company.

$$CCEP_{EI} = w_R R + w_G G \tag{2}$$

where

w_R – Importance weighting of regional environmental impact main category

R – Regional environmental impact main category score w_G – Importance weighting of global environmental impact main category

G – Global environmental impact main category score $CCEP_{EI}$ – Coal consumption and energy production environmental indicator score

In the final step, according to the results of the current CCEP environmental performance indicator score calculations, a set of thresholds must be defined that can assist the DMs in improving the evaluation system. These decisions are about various improvement scenarios that can be implemented in the current system. Afterward, these improvement and analysis scenarios should be re-examined/evaluated, and a new indicator should be obtained.

4. Case application and results

4.1. A Chinese coal-to-energy supply chain

China, as the world's major coal producer and consumer, emits large amounts of CO_2 and other environmental hazards (Sun et al., 2018). In recent research conducted by Yang et al. (2019), the drivers of coal overcapacity in China from both the supply and demand sides have been analyzed and some policy implications are put forward to tackle these issues. The Chinese coal-to-energy SC considered in the current work is shown in Fig. 2 (a). Due to data availability, we only considered coal mine X (energy production side) and coal-fired power plant M (coal consumption side) in Fig. 2 (a). Both plants are local state-owned enterprises and located in Zaozhuang, which is a mining city, belonging to the Shandong province of China.

After coal is extracted from coal mine X, it is transported to the following: coal-fired power plant M (15% of yield) in Zaozhuang, steel group A (23% of yield) in Nanjing, steel group B (20% of yield) in

Shanghai, coking plant C (15% of yield) in Rizhao, coking plant D (7% of yield) in Weifang, and other small enterprises (approximately 20% of yield). For the coal-fired power plant M, most of the coal comes from coal mines Y and Z, which account for 80% of the coal consumption, and the remaining 20% comes from coal mine X (coal mines Y and Z provide most of the coal owing to the inexpensive coal prices in the Shanxi province). The complete coal-to-energy SC is shown in Fig. 2 (b). Here, we only studied the coal-to-energy SC from coal mine X to coal-fired power plant M due to data availability. The extracted coal from coal mine X is transported 64 km by heavy truck to be combusted at coal-fired power plant M. In part, coal mine X is used as a source for coal due to insufficient rail capacity and administrative factors for other sources. Three processes in the coal-to-energy SC can be characterized in this case study: i) the coal-mining process or coal production stage, ii) the coal transportation process, and iii) coal consumption at the power plant to generate electricity, as shown in Fig. 2 (c).

4.2. Scope and system boundary

Life cycle assessment often utilizes a cradle-to-grave boundary for evaluating industrial products and systems. A cradle-to-grave life cycle commences with extracting the raw materials and continues with manufacturing product(s); then, the end consumers (industrial or individuals) consume the manufactured product(s), and the cycle is completed with the return of the used product(s) to the environment (Balaguera et al., 2018). The developed framework starts with coal production and ends with coal consumption, as shown in Fig. 3. The boundary of the analysis is defined based on this cradle-to-grave perspective. The main reason for this boundary is the nature of the case system, which represents a “Mining-to-Product (MTP)” system. This indicates that the end-of-life stage of the coal life cycle (recycling stage) is not considered in the current application. The coal-to-energy SC processes under study consist of the coal-mining process, coal washing and selection process, coal transportation process and coal combustion process. The functional unit (FU) is denoted as 1 kW-hour of energy produced. In this research, an FU is defined as 1 kW h.

4.3. Life cycle inventory analysis

Inventory analysis plays a central role in an LCA (Ding et al., 2017). According to the system boundary described in Fig. 3, a brief description of the three principal processes is provided. For a detailed introduction to material inventory and energy inventory in each process, please refer to the studies of Wang (2011) and Wang and Mu (2014).

The *coal-mining process* in coal “mine X” is an underground mining operation. This operation includes drilling, loading, hauling and more. Ventilation, lighting, and communications are some of the secondary operations in this coal mine. Mine X generated 3.4 million tonnes of raw coal in 2012. In addition, it used 521.22 thousand cubic meters of fresh water, 147.90 tonnes of diesel oil, 37.16 tonnes of petrol, 434.52 tonnes of steel, 19.7 thousand tonnes of cement, 155.41 cubic meters of timber, and 15.54 tonnes of ANFO (ammonium nitrate AN and fuel oil). For internal use, 7.23 million kWh of electricity and 13.2 thousand tonnes of coal were consumed.

Along with the abovementioned operations, the coal-mining process of mine X also encompasses coal preparation/cleaning. The reduction of the extracted coal size and removal of rocks and fines from the extracted coal are performed during the coal preparation activity. Mine X uses a gravity method to clean the coal. In this task, harmful impurities settle to the bottom after a coal flotation process on the surface. Finally, the purified coal is transported to the locations of the coal-fired power plants.

In China, the *coal transport process* is typically completed via railways, highways, or waterways. In this study, the transported ammonium nitrate, ammonia (NH_3), hydrogen chloride (HCl), sodium hydroxide (NaOH), and calcium carbonate ($CaCO_3$) are not included while constructing the life cycle inventory. According to the investigation, from mine X to power plant M, the coal is shipped by FAW Jiefang Hanwei heavy trucks with a capacity of 40 tonnes. These trucks usually carry approximately 50 tonnes. The distance from mine to the power plant is 64 km, and the diesel fuel consumption for a round trip is 36.5 L.

The *coal combustion process* constitutes the burning process occurring at a coal-fired power plant. The total installed capacity of the power plant is 1225 MW, and the power generation is 8.39 billion kWh. In 2012, plant M consumed

(1) 1.91 million tonnes of raw coal,
(2) 1.62 million tonnes of coal gangue,
(3) 2.76 million tonnes of coal slurry, and
(4) 58.30 million tonnes of fresh water.

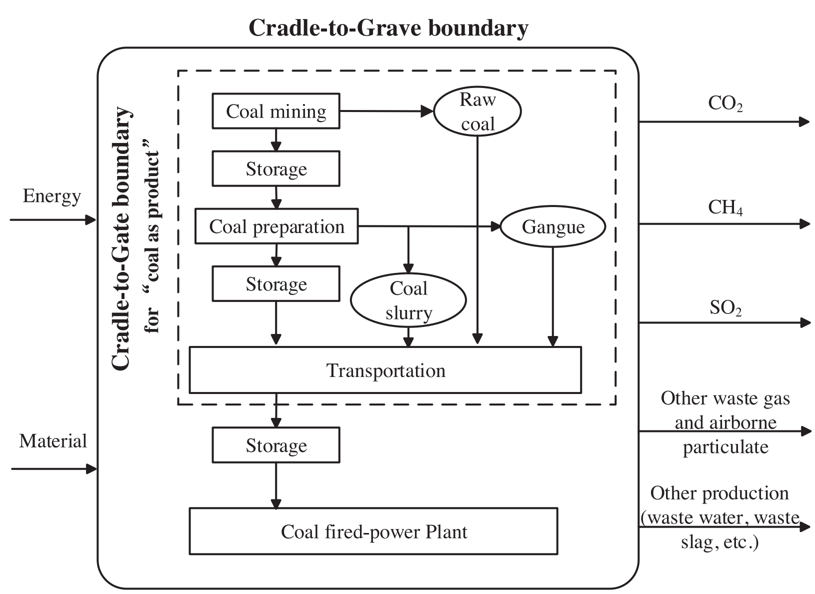

Fig. 3. Cradle-to-grave system boundary of the coal-to-energy SC.

4.4. Life cycle impact assessment

All results are based on the reference FU of 1 kW h of electricity. Five sub-categories have been selected, and Gabi 4′s CML 2001 is adapted to calculate the environmental impacts related to these sub-categories, i.e., acidification potential (AP), ozone depletion potential (ODP), global warming potential (GWP), eutrophication potential (EP), and photochemical oxidants creation potential (POCP). When estimating environmental impacts, GWP and ODP are classified within the global environmental performance main category. EP, AP, and POCP are categorized as regional environmental performance main categories (Kim et al., 2016).

AP is defined by acid deposition (H^+) measurement of HF, NO_x, NH_3, SO_2, and HCl. ODP measures the ozone layer depletion potential mostly concerned with chlorofluorocarbon (CFC) compounds and other halogenated hydrocarbons emissions. GWP is derived by considering an aggregated amount of greenhouse gas (GHG) emissions and their GWP factors, respectively. The gases that contribute to GWP are mainly CO, CO_2, CH_4, and N_2O. EP is described as the potential of nutrients to cause toxin production and eutrophication. POCP is described as the potential to generate summer smog and photochemical oxidants from volatile organic compounds (VOCs) and oxides of nitrogen. This value is articulated relative to the POCP classification factor for ethylene. The GWP, EP, POCP, AP and ODP raw impact assessment values with respect to the three considered processes in the coal-to-energy SC are shown in Table 2.

4.5. Weighted fuzzy inference system model implementation

4.5.1. Sub-category importance weight calculations

In this phase, Chang's FAHP (Chang, 1996) was used to weight the global and regional sub-categories. Hence, the experts (the production manager and scheduling manager in coal mine X and the production manager and materials manager in power plant M) were asked to make the pairwise comparisons based on the scale shown in Table 3. Then, using the FAHP steps, the final weights of the environmental sub-categories were calculated. These calculation steps are not shown in this article owing to limitations on space.

Table 4 tabulates the derived weights separately for global and regional main categories.

4.5.2. Fuzzy evaluation mechanism

The crisp values of the environmental sub-categories (input variables) are transformed into MF grades. Then, a target range is configured for each of these input linguistic variables, as shown in Table 5. For each of the linguistic variables, the constructed linguistic MFs allocated to the formulated fuzzy sets are displayed in Table 5. In this paper, a TFN is utilized in the developed FIS model for the environmental impact sub-categories (input variables). The numerical inputs for this fuzzy mechanism are then fuzzified based on a comprehensive knowledge consisting of various weighted fuzzy rules. As explained in Sub-section 3.2, the importance weights of each sub-category (shown in Table 4) cannot be incorporated in the fuzzy evaluation mechanism using the traditional FIS model. Therefore, a heuristic approach was developed in this research work to resolve this issue (see Sub-section 3.2). Applying the importance weights directly to the input variables would result in alteration of the crisp input values which is not desirable. Instead, using the proposed heuristic, these weights are incorporated in defining the fuzzy rules. Some realistic rules have been constructed based on the four DMs' knowledge. Table 6 tabulates some sample fuzzy rules for illustration purposes.

The following calculations demonstrate the applicability of the developed heuristic in constructing the fuzzy rule base while incorporating the importance weights of each input variable (sub-categories). Consider rule number 5 in Table 6, which reads "IF EP is L AND

Table 3
The linguistic variables and triangular fuzzy numbers (TFNs).

Linguistic variable	TFN	Reverse TFN
Equal importance	(1, 1, 1)	(1, 1, 1)
A little more important	(0.5, 1, 1.5)	(0.66, 1, 2)
More important	(1, 1.5, 2)	(0.5, 0.66, 1)
Much more important	(1.5, 2, 2.5)	(0.4, 0.5, 0.66)
Absolute importance	(2, 2.5, 3)	(0.33, 0.4, 0.5)

Table 4
Environmental sub-category importance weights.

Main category	Sub-category	Importance weights
Global environmental performance	GWP	0.7036
	ODP	0.2964
Regional environmental performance	EP	0.454
	PCOP	0.321
	AP	0.225

Table 5
Fuzzy sets and their linguistic MFs.

Linguistics MF	Fuzzy set	Linguistics MF	Fuzzy set
Regional environmental performance		*Global environmental performance*	
Linguistics variable: AP		Linguistics variable: GWP	
Low	[-3.58 1.78 7.14]	Low	[492 872 1250]
Medium	[1.78 7.14 12.5]	Medium	[872 1250 1628]
High	[7.14 12.5 17.86]	High	[1250 1628 2010]
Linguistics MF	Fuzzy set	Linguistics MF	Fuzzy set
Regional environmental performance		*Global environmental performance*	
Linguistics variable: EP		Linguistics variable: ODP	
Low	[-0.0755 0.103 0.2815]	Low	[-8.642 0.072 8.786]
Medium	[0.103 0.2815 0.46]	Medium	[0.072 8.786 17.5]
High	[0.2815 0.46 0.6385]	High	[8.786 17.5 26.21]
Linguistics MF	Fuzzy set		
Regional environmental performance			
Linguistics variable: POCP			
Low	[-0.287 0.017 0.321]		
Medium	[0.017 0.321 0.625]		
High	[0.321 0.625 0.929]		

Table 2
Environmental impact of coal-to-energy SC based on 1 kW h of electricity generated.

Category	Coal extraction process	Transportation process	Combustion process	Coal-to-energy SC	Target range	Unit
GWP	130.4742	17.5391	1169.7123	1317.7256	[872-1628]	g CO_2-Equiv.
EP	0.0368	0.0084	0.3120	0.3572	[0.103-0.460]	g PO_4^{3-} Equiv.
POCP	0.0401	0.0072	0.4673	0.5147	[0.017-0.625]	g C_2H_4-Equiv.
AP	0.2494	0.0981	4.9119	5.2594	[1.78-12.5]	g SO_2-Equiv.
ODP	6.8785	0.6946	6.7809	14.3539	[0.072-17.5]	μg R_{11}-Equiv.

Note: Target ranges required for the FIS model are extracted and refined from related literature (Atilgan and Azapagic, 2015, 2016; Dones et al., 2007; Korre et al., 2010; Rakotoson and Praene, 2017; Şengül et al., 2016; Skone and James, 2010; Stamford and Azapagic, 2012; Widder et al., 2011).

Table 6
The knowledge rule base for the two main categories.

Rule No.	Regional and Global environmental performance rules
1	IF GWP is **L** AND ODP is **L** THEN Global environmental performance is **H**.
2	IF GWP is **L** AND ODP is **H** THEN Global environmental performance is **MH**.
3	IF GWP is **H** AND ODP is **M** THEN Global environmental performance is **LM**.
4	IF EP is **H** AND PCOP is **M** AND AP is **low** THEN Regional environmental performance is **M**.
5	IF EP is **L** AND PCOP is **L** AND AP is **H** THEN Regional environmental performance is **MH**.
6	IF EP is **H** AND PCOP is **L** AND AP is **H** THEN Regional environmental performance is **LM**.
7	IF EP is **M** AND PCOP is **L** AND AP is **M** THEN Regional environmental performance is **MH**.

Table 7
A sample calculation procedure for fuzzy rule definition.

	EP	PCOP	AP	Output value
MF score, A_i	1	1	3	
Importance weight, W_i	0.454	0.321	0.225	
$W_i A_i$	0.454	0.321	0.675	$\sum_{i=1}^{m} W_i A_i = \mathbf{1.45}$

PCOP is L AND AP is H THEN Regional environmental performance is MH". According to the proposed heuristic, the corresponding MF numbers in the assessment process would be 1, 1 and 3. Based on the proposed heuristic in Sub-section 3.2, the calculation process was performed and is shown in Table 7. The obtained aggregated value of 1.45 means that the output MF for regional environmental performance main-category should be medium to high as the value of 1.45 is located in the 1–1.66 range.

Following the developed heuristic procedure, the experts' knowledge was translated into weighted linguistic fuzzy rules for each subcategory. Eq. (1) calculates the number of constructed rules for each main category. The global environmental performance main category has nine rules while the regional environmental performance main category requires 27 rules.

The computed fuzzified outputs are then defuzzified into a crisp number using the constructed MF scaling from zero to one. The computed output values that are closer to zero indicate a low regional or global environmental performance. In contrast, the output values closer to one are considered as a high regional or global environmental performance. The output variables (regional and global environmental performance) are transformed into MFs, as shown in Table 8. The final calculated score serves as an indicator reflecting the environmental performance state of the evaluated CCEP process. This score was calculated using Eq. (2) and the results are presented in Table 9.

The proposed FIS model was implemented utilizing the MATLAB fuzzy logic package. Two threshold values (0.33 and 0.66) were devised to facilitate decision making about various improvement scenarios in the current coal-to-energy SC processes. These thresholds were defined based on the decision makers' expert opinions and as a result of discussions with the current authors of this research article. Based on these discussions, if the obtained CCEP environmental performance indicator score ranges from 0 to 0.33, the current environmental performance is not satisfactory and requires a comprehensive redesign of the production and consumption stages of the coal-to-energy SC process. A CCEP

Table 8
Regional and global fuzzy sets and their linguistic MFs.

Linguistics MF	Fuzzy set	Linguistics MF	Fuzzy set
Linguistics variable: *Regional environmental performance*		Linguistics variable: *Global environmental performance*	
L	[-0.25 0 0.25]	L	[-0.25 0 0.25]
LM	[0 0.25 0.5]	LM	[0 0.25 0.5]
M	[0.25 0.5 0.75]	M	[0.25 0.5 0.75]
MH	[0.5 0.75 1]	MH	[0.5 0.75 1]
H	[0.75 1 1.25]	H	[0.75 1 1.25]

environmental performance indicator score between 0.33 and 0.66 is considered to be performing normally, but some minor improvements should still be investigated to improve the performance. If the indicator score is calculated between values of 0.66 and 1, it will be considered as an environmentally high-performing SC. For each of these ranges, the experts' advice was expressed based on focus group meetings with DMs inside the case organization to devise appropriate improvement scenarios.

In the base scenario for the coal-to-energy SC under investigation, the CCEP environmental performance has been determined as "medium performance" with an indicator score of 39.15%. Based on this indicator score, the DMs suggested additional scenarios (redesign, equipment replacement, etc.) to improve the performance. These scenarios and their outcomes are provided in the next section.

5. Analysis and comparison of alternative scenarios

In this section, a scenario-based analysis is performed to identify alternative paths to mitigate the environmental impact of the studied coal-to-energy SC. Various possible scenarios were discussed among the experts and the most important ones were chosen for further consideration. The amount of coal required at a CFPP is highly dependent on the current efficiency of the plan. Therefore, one important analysis was discussed that would test the sensitivity of environmental performance when experiencing lower or higher plant efficiency. This analysis is particularly important, as the CFPP efficiency level has direct impacts on coal mining and transportation processes. On the other hand, scenarios such as improving the transportation modes and traveled distance were seen as trivial in the current round of improvements, as they impact only the coal transportation process emissions. Finally, three alternative scenarios were put forward by the DMs. They were interested in finding the extent to which these modifications can change the environmental performance of the entire coal-to-energy SC.

5.1. Scenario-based analysis

5.1.1. - Alternative scenario 1: capture and use coal mine methane (CMM)

Based on the Chinese safety code: specification for identification and classification of gassy mines (State Administration of Coal Mine Safety of China, 2006), mine X is categorized as a slightly gassy mine. Due to the low concentration of CMM, it is discharged to the atmosphere under the current situation. Hence, the utilization of CMM as an energy source is close to zero. The main reason for this low utilization rate is that mine X has not yet invested in the required technology to utilize the CMM emitted in the various processes associated with coal mining. Although the goal of the 11th China five-year plan (FYP) is to utilize 60% of CMM, the utilization efficiency was approximately 30% for 2004–2009 (Cheng et al., 2011). Hence, as the first alternative scenario, this paper considers the assumption that the capture and usage of CMM as a source of energy for heating can reach 30%. The raw impact assessment results are shown in Table 10. These results are utilized as the input data to implement the FIS model. The obtained CCEP performance indicator score for this scenario is presented in Table 10. Under the assumption that the capture and use of CMM as an

Table 9
Results of the base scenario and three improvement scenarios.

Score	Coal-to-energy SC	30%(utilization rate of coal mine methane)	37.5% (current efficiency of CFPP + 0.5%)	36.5%(current efficiency of CFPP -0.5%)
Global environmental performance	0.432	0.450	0.444	0.418
Regional environmental performance	0.351	0.363	0.352	0.349
CCEP environmental performance indicator score	0.391	0.406	0.398	0.383

Table 10
Life cycle impact assessment results for alternative scenario 1.

Category	Coal-to-energy SC	Capture and use of CMM as an energy source is 30%	Unit
GWP	1317.7256	1298.3847	g CO_2-Equiv.
EP	0.3572	0.3586	g PO_4^{-3}-Equiv.
POCP	0.5147	0.4905	g C_2H_4-Equiv.
AP	5.2594	5.2813	g SO_2-Equiv.
ODP	14.3539	14.3857	μg R_{11}-Equiv.

energy source in the coal-mining process is 30%, the global, regional, and CCEP environmental performance indicators in the coal-to-energy SC have changed by 1.8%, 1.2%, and 1.5%, respectively.

5.1.2. - Alternative scenarios 2 and 3

The DMs inside the power plant wanted to determine how a modification in the combustion process at the CFPP would affect the environmental performance of the whole coal-to-energy SC. Therefore, this was investigated in more detail by increasing and decreasing the overall efficiency of the CFPP. The CFPP efficiency for plant M was 37% in the base case scenario. The efficiency of the CFPP was changed by plus or minus 0.5%, i.e., 37.5% and 36.5% for the system. The developed LCA-FIS was implemented to simulate the extent to which these modifications affect the overall CCEP indicator. The raw impact assessment results of these two alternative scenarios are shown in Table 11 with the recalculated CCEP environmental indicators tabulated in Table 9. It is found that a 0.5% increase in efficiency of the CFPP yields 1.2% improvement in global environmental performance but only 0.1% improvement in regional environmental performance. These improvements would lead to a 0.65% increase in overall CCEP environmental performance indicator score compared with the base case.

Alternatively, a 0.5% decrease in efficiency of the CFPP would yield a 0.8% lower overall CCEP environmental performance score compared with the base case. Consequently, these findings show the magnitude of the changes that a decrease in the efficiency of the CFPP can have on the CCEP environmental performance compared with an increase in this efficiency. By comparing the results of alternatives 1 and 2, it can be concluded that realizing a 30% utilization of CMM is more effective than a 0.5% change in the CFPP efficiency in improving the environmental performance of the coal-to-energy SC.

Despite a Chinese government proposal on *Administrative Provisions on Projects of Clean Development Mechanism*, and regulatory tactics with regards to taxation and compensation that seek to promote environmental improvement, these regulatory approaches have not yet achieved their desired goal (Cheng et al., 2011). The low-concentration methane and other constraints limit local state-owned coal mines, such as mine X, from purchasing a methane drainage system. Other solutions would need improvements in technologies relating to the drainage and exploitation of low-concentration methane.

Table 11
Life cycle impact assessment results for alternative scenarios 2 and 3.

Category	37.5% (+0.5%)	36.5% (−0.5%)	Unit
GWP	1300.8823	1338.5394	g CO_2-Equiv.
EP	0.3524	0.3626	g PO_4^{-3}-Equiv.
PCOP	0.5086	0.5234	g C_2H_4-Equiv.
AP	5.2034	5.3540	g SO_2-Equiv.
ODP	13.8956	14.7697	μgR_{11}-Equiv.

Regarding the overall efficiency of CFPPs, several possibilities would be expected to increase the CFPPs efficiency such as equipment overhaul and upgrades, and enhanced maintenance operations scheduling. The U.S. National Energy Technology Laboratory (NETL) presented a list of potential approaches to improve and recover the overall efficiency of CFPPs (DOE—National Energy Technology Laboratory, 2008). One possible approach can be replacing old equipment with new equipment within a CFPP (Campbell, 2013). However, this approach is deemed not to be practical due to the expected high investments that could not be justified by the marginal amount of calculated environmental performance improvement in this case study. Instead, for plant M a financially viable option to increase thermal efficiency was discussed, i.e., to retire low-efficiency equipment together with more generation from high-efficiency overhauled equipment. Moreover, an advanced prognostic maintenance operation must be investigated in more detail to optimize the scheduling of equipment refurbishing processes.

5.2. Comparison

The developed CCEP environmental indicator was compared to the traditional unweighted LCA-FIS approach (Table 12) using the base case study. The main purpose of performing this comparison was to demonstrate the effect of assigning importance weightings on the input variables (environmental sub-categories) using the proposed heuristic model (weighted LCA-FIS approach). The results show that there is a meaningful difference in the CCEP scores, especially in those for global and regional environmental performance. When applying the DMs' weights for GWP and ODP, the global environmental performance score decreased substantially compared to the traditional unweighted LCA-FIS result (5.4%). Conversely, the regional environmental performance score slightly increased when the EP, PCOP, and AP weightings were applied using the weighted LCA-FIS model (0.9%). From this analysis, it is found that the proposed LCA-FIS environmental performance framework is a useful tool for considering the sub-category weightings.

6. Theoretical and managerial implications

This study seeks to contribute to reducing the environmental impact of consumption and production practices in a coal-to-energy SC by creating a performance indicator and exploring system changes. In the integrated consumption and production practices literature, Wang et al. (2018) highlighted that the investigation of integrated consumption and production practices performance measurement is still at its early stages. They found only a few activities that focused on developing mathematical and life cycle-based approaches for integrated consumption and production environmental performance assessment and recommended that future research should be cultivated in this domain. In a recent review of LCA methodology by Onat et al. (2017), it was highlighted that broadening the scope of the assessment from the product level to the system level, development of the uncertainty analysis

Table 12
Comparison results.

	Weighted LCA-FIS score	Traditional unweighted LCA-FIS score
Global Environmental performance	0.432	0.486
Regional Environmental performance	0.351	0.342
CCEP environmental performance indicator score	0.3915	0.414

mechanisms and involvement of key stakeholders in the assessment procedure would add to the reliability of the LCA results. Similarly, Awuah-Offei and Adekpedjou (2011) emphasized the challenges associated with risk and uncertainty associated with the mining industry and highlighted the inclusive need for rigorous uncertainty analysis to be overcome in an LCA framework.

Within these contexts, the current research work narrows these theoretical gaps by proposing an integrated weighted LCA-FIS framework to measure the environmental performance of a coal-to-energy SC. Unlike the traditional LCA methodology which only provides the environmental burdens of a considered process or product, the proposed framework in this study utilizes the main steps of the LCA method but replaces its normalization and weighting stages with a proposed weighted FIS model. The integrated framework overcomes the deficiencies of the traditional LCA methodology by providing an environmental indicator score that can be utilized to enhance decision-making for the evaluation of improvement opportunities.

The proposed framework addresses a deficiency in the traditional LCA methodology. Although the LCIA results of the traditional LCA methodology provide insights into the amount of environmental burdens, the DMs inside the case organizations often face difficulties in using the results to devise improvement scenarios. The main reason for this difficulty has been the lack of a quantitative measure of the extent of how well or poorly their coal-to-energy SC processes are performing. From a managerial point of view, these shortcomings of the LCA framework can increase the uncertainty in utilizing the results from the traditional LCA methodology. Toward this end, an integrated LCA-FIS framework was proposed in this research work to measure the environmental performance of the various coal-to-energy SC processes with less uncertainty and the inclusive involvement of the key stakeholders inside the case organization.

7. Conclusion

In recent years, CCEP has received increasing attention owing to airborne emissions from CFPPs. CFPPs play a dominant role in the power sector worldwide. In China, coal is expected to retain its primary energy position (70%) over the next few decades. This is mainly because of its stable supply and abundant reserves in China. However, CCEP also accounts for a huge share of CO_2 emissions and other environmental hazards, such as SO_2 and NO_x. Therefore, understanding the environmental implications of the coal life cycle from its production in coal mines to its consumption at CFPPs is an essential task.

The continued role of coal in the power sector highlights the importance of an accurate environmental indicator for coal-to-energy SC processes to enhance decision and policy-making processes. The need for such an indicator was identified upon reviewing the literature related to LCA approaches to CCEP. This gap in the literature was reinforced in the initial steps of performing a traditional LCA study at the case company site. The company DMs highlighted that the resulting environmental burdens of a traditional LCA would not provide proper decision-making assistance. In other words, although the traditional LCA approach provides a normalized environmental burden value for a process or product, the DMs experience difficulties in understanding the numerical level of the environmental performance of such a process or product.

In this paper, an environmental performance assessment framework was proposed to serve as a practical decision-making system in evaluating the impacts of CCEP practices on the environment. The framework encompasses two phases, with the first phase commencing by defining the analysis objectives and scope together with establishing a life cycle inventory for the identified main processes. This is followed by the characterization process to produce an aggregated impact score with respect to the five identified environmental sub-categories. Then, the calculated raw impact results are processed using a proposed weighted FIS model, forming the second phase.

The main contribution of the developed integrated framework is its ability to provide a definitive environmental indicator score for a typical coal-to-energy SC. Based on the proposed weighted FIS model, the normalization process of the sub-categories impact scores in LCA is enhanced by using a set of target ranges for each environmental sub-category. Furthermore, the application of the proposed framework to an actual coal-to-energy SC is another contribution of this paper. One of the advantages of the developed weighted FIS model is its ability to deal with the importance weighting of the sub-categories (input variables).

One of the limitations of this study is related to the boundary of analysis, which does not specifically deal with the end-of-life phase of the coal life cycle. One possible future research direction would be to extend the boundary of the analysis to include the management and treatment of coal combustion by-products. Moreover, further research needs to be conducted to develop a life cycle sustainability assessment framework that incorporates other dimensions of sustainability, such as economic and social aspects. Possible integration of the developed framework with perpetual LCA software is currently under investigation. This integration would yield a huge advantage to industrial practitioners in terms of usability and effectiveness. Other future works in the field of LCA can consider the SCs as complex adaptive systems and can account for time and other dynamics variances by using technologies such as agent-based modeling and analysis.

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