Development of a Multi-Criteria Indicator for Product Life Cycle Decision-Making

Yong Han Kim[a*], Sidi Deng[b], Thomas Maani[a], Matthew J. Triebe[c], Nehika Mathur[c], John W. Sutherland[a]

[a]School of Sustainability Engineering and Environmental Engineering, Purdue University, West Lafayette, IN 47907, USA

[b]Engineering Design Division, State University of New York at Binghamton, 4400 Vestal Parkway East, Vestal, NY, USA

[c]National Institute of Standards and Technology, 100 Bureau Dr. Gaithersburg, MD 20899, USA

* Corresponding author. Tel.: +1-765-496-9697; fax: +1-765-494-4482. E-mail address: kim3822@purdue.edu

Abstract: Maximizing product value and resource efficiency has been widely regarded as a key objective throughout the product life cycle, supported by improved product designs, informed manufacturing decisions, and regenerative approaches. Although the evaluation of life cycle performance is widely recognized as a critical aspect, there remains a lack of indicators that comprehensively characterize multi-dimensional performance across different product life cycle stages. To address this gap, this study develops a novel indicator, the Life Cycle Performance Indicator (LCPI), which integrates multiple dimensions (economic efficiency, pollutant release level, and workforce stability) into a single compound measure using the Fuzzy Analytic Hierarchy Process (FAHP) to identify specific life cycle stages that require performance improvement. The proposed indicator is applied in a case study of a diesel engine remanufactured into an LNG engine at the end of a use cycle to pinpoint life cycle stages most in need of performance improvement, enabling effective and focused interventions. Scenario-based analysis indicates that the LCPI could potentially be improved by up to 60%, indicating the need for strategic changes in life cycles to achieve this gain. This study demonstrates the use of the developed indicator and provides decision-makers with the ability to gain quantitative insights while integrating multiple dimensions simultaneously.

Keywords: Multicriteria decision-making, Fuzzy Analytic Hierarchy Process (FAHP), Compound indicator, Life cycle performance evaluation

1. Introduction

The pursuit of economic advantages has always been a key aspect in decision-making, and its significance has become even more pronounced in recent years due to changing material costs, supply chain issues, and the growing need for resilient business models (Raoufi et al., 2024). These concerns have led manufacturers to rethink traditional production models and explore alternative approaches that offer additional economic benefits (Okorie et al., 2023). They have started to incorporate approaches that improve material utilization, reduce material purchasing expenses, and extend product lifespans, leading to greater economic advantages and prompting them to reconsider how value is further retained throughout the product life cycle

(Pruhs et al., 2024). Thus, how to design processes, products, and life cycles has become a key question for manufacturers seeking to extend product value and generate new revenue streams.

Different approaches that extend a product's life such as better maintenance practices, remanufacturing and recycling, could offer ways of maximizing product value and greater material utilization. For instance, remanufacturing could restore a used product into a "like-new" condition, performing comparably to new ones and providing an opportunity to re-enter the market at lower costs (Vogt Duberg et al., 2020). In many cases, remanufacturing remains more economical than producing new items, particularly when reverse logistics and collection costs are efficiently managed (Ullah et al., 2021). This creates new opportunities to sell remanufactured products in secondary markets, which can increase the profitability of manufacturers (Cao et al., 2023). Recycling could recover materials from end-of-life (EoL) products, reducing the need to purchase new raw materials and lowering dependence on external suppliers (Mathur et al., 2024). Using recycled materials could substantially lower production costs as they may consume less energy compared to extracting and refining virgin materials (Howarth et al., 2014). Also, recovered materials can be sold in ssecondary markets, which could help to reduce waste management costs (Goksal, 2022).

In addition to economic factors, the increasing global attention to pollutant-related and human safety issues has motivated companies to embrace a broader perspective on regenerative production models. The concept of regenerative production is being explored as a means to create products in ways that are more economically profitable, less associated with pollution and health concerns and provide greater well-being for employees and communities (Garretson et al., 2016; Haapala et al., 2013). Driven by this approach, there is a realization of the need to shift from traditional linear product life cycle models, which follow "take-make-dispose" approach, to regenerative life cycle models that put products and materials back into the loop as shown in Figure 1 (Fatimah et al., 2023). By implementing practices such as recycling and remanufacturing, numerous benefits such as preserving product value, reducing resource consumption, minimizing waste, and promoting economic savings can be achieved (Murray et al., 2017; Ravikumar et al., 2024; Yang et al., 2023). To successfully address the various aspects associated with this transition to regenerative production models, effective approaches must be implemented, as they are crucial for maximizing the product value and resource efficiency (Garetti & Taisch, 2012; Geissdoerfer et al., 2017).

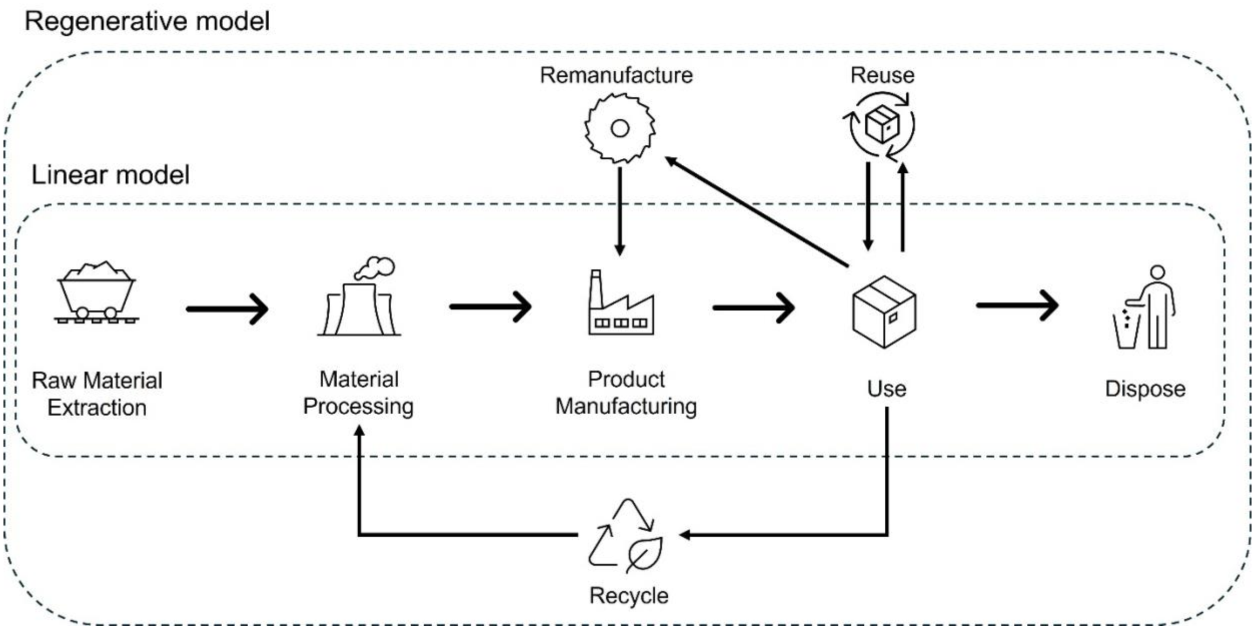

Fig. 1. Maximizing product value: A life cycle perspective

Appropriate indicators for gauging life cycle performance are needed to provide quantifiable measures to support progress-tracking and guide decision-making within business operations (Kim et al., 2022). These indicators can serve as valuable tools for setting benchmarks, helping to shape strategies, and identifying areas for improvement (Genovese et al., 2017). Moreover, they offer an overview of how well companies align with their defined performance objectives, identifying where resources should be allocated more effectively (Haupt & Hellweg, 2019; Rocchi et al., 2021). While various indicators have been developed to assess specific dimensions of life cycle performance, an indicator that simultaneously evaluates multiple dimensions across each stage of a product's life cycle remains absent. This absence constrains the ability to accurately evaluate life cycle performance at each stage, limiting the identification of areas where intervention is most needed. Furthermore, understanding how adjustments across multiple dimensions can synergistically enhance overall life cycle performance remains insufficiently explored.

To address the research gap, a compound indicator, the Life Cycle Performance Indicator (LCPI), is developed to assess the degree of value maximization at each product life cycle stage. This comprehensive indicator incorporates multiple dimensions (economic efficiency, pollutant release level, and workforce stability) to identify life cycle stages that need performance improvement. Moreover, this study examined how changing the emphasis on different dimensions (economic efficiency, pollutant release level, and workforce stability) jointly affects overall life cycle performance, which has not been sufficiently explored in existing research. To consider multi-dimensional aspect, a Fuzzy Analytic Hierarchy Process (FAHP) method is employed, which is a commonly used technique for multi-attribute decision-making (Chan et al., 2008; Lee et al., 2008). As a case study, the life cycle stages of an EoL diesel engine that can be remanufactured into a Liquefied Natural Gas (LNG) engine are analyzed. The holistic process chain is studied from raw material production, material transportation, diesel engine manufacturing, diesel engine use, and back to remanufacturing into LNG engines, essentially “closing the product loop.”

The rest of the paper is structured as follows. Section 2 provides an overview of existing literature on product value maximization efforts and discusses the need for a comprehensive indicator to evaluate factors influencing the value of manufactured products throughout their life cycle. Section 3 describes the Fuzzy Analytic Hierarchy Process (FAHP) methodology and explains how the developed compound indicator is calculated. Section 4 introduces the selected criteria for Multi-Criteria Decision Analysis (MCDA) and presents their calculated weights. Section 5 demonstrates the application of the proposed indicator through a case study, illustrating how the findings can inform decision-making and identify stages of the product life cycle that require performance improvement. Finally, Section 6 concludes the paper by summarizing the key findings and highlighting the contributions of this study.

2. Literature review

Businesses are increasingly recognizing the significance of maximizing product value and achieving high material efficiency. Many firms have begun to place greater emphasis on these factors, acknowledging the influence of a life cycle engineering perspective on maintaining healthy long-term operations and strengthening corporate reputation (Saunila et al., 2024). In addition to the traditional considerations of economic aspects, incorporating pollutant-related and human health considerations into their overall product strategy has become more critical for companies to maintain their competitive advantage in recent years (Adams et al., 2016; Clementino & Perkins, 2021; De Pascale et al., 2021; Duque-Grisales & Aguilera-Caracuel, 2021; Gillan et al., 2021; Singhania & Saini, 2023). As the importance of a broader view of what constitutes a “high performing” life cycle continues to rise, companies are recognizing the need for tools that can monitor their progress to align with industry standards and compare against industry peers (Machado et al., 2020).

Given this realization, various efforts have been undertaken to quantify life cycle performance across different domains, including renewable energy (Evans et al., 2009), supply chain (Hutchins & Sutherland, 2008), and smart manufacturing (Lu et al., 2016). Deng et al. evaluated the economic performance of a gas-assisted microflow extraction process for recovering valuable metals from electronic wastes utilizing a techno-economic assessment (TEA) model (Deng et al., 2023). Kwak and Kim suggested an integrated pricing and production planning model to optimize production planning, sales pricing, and buyback pricing, maximizing total profit for new and remanufactured products (Kwak & Kim, 2017). Peŕez-Cardona et al. conducted a comparative LCA and TEA of magnet recovery from hard disk drives (HDDs) and investigated favorable scenarios that maximize product value under uncertainty (Peŕez-Cardona et al., 2025). Jung et al. proposed a method to assess health risks to individuals near a construction site resulting from the dispersion of PM10 particles (Jung et al., 2019). Chen et al. investigated the health risks posed by dust and noise exposure among laborers, focusing on the intensity and frequency of exposure in construction work (Chen et al., 2022).

In addition to quantification efforts, researchers have developed various indicators as analytical tools applicable to different sectors. For instance, Azapagic proposed a set of indicators for the mining and minerals sector to measure and improve performance by integrating various aspects, designed to identify areas for improvement and enhance stakeholder engagement through reporting (Azapagic, 2004). Choi and Sirakaya employed a modified Delphi method to establish indicators that assess community tourism across multiple dimensions, measuring its progress and impact (Choi & Sirakaya, 2006). Hutchins et al. constructed a framework for assessing the human and stakeholder related aspects of corporate performance in the U.S. context and proposed indicators using the Delphi method and Maslow's hierarchy of needs (Hutchins et al., 2019). Brundage et al. proposed a set of indicators to identify areas in the manufacturing line that have energy inefficiency (Brundage et al., 2016). Mota et al. introduced an indicator to evaluate strategic decisions that consider the impact of political issues on a company's performance (Mota et al., 2015). Ghadimi et al. developed an indicator using LCA and fuzzy inference system (FIS) to assess coal usage and energy production (Ghadimi et al., 2019).

Despite growing research on life cycle performance quantification and indicators, the development of standardized evaluation methods that holistically capture multiple influencing factors (e.g., economic and human health/safety) remains a main challenge (Enyoghasi & Badurdeen, 2021; Escoto et al., 2022; Mathur et al., 2023). The absence of a widely accepted evaluation tool creates inconsistencies in measuring life cycle performance, making it difficult to establish clear benchmarks (Huovila et al., 2019). To address this issue, several studies have explored methodologies to assess various performance aspects at a system-level using the Fuzzy Analytic Hierarchy Process (FAHP) method (Ghadimi et al., 2012; Singh et al., 2018). However, these studies i) did not provide the granularity needed to determine which specific phases (e.g., distinct stages of a product's life cycle) require performance improvement, and ii) did not investigate how variations in evaluation dimensions affect overall life cycle performance results and reveal trade-offs among them. Therefore, the present study aims to address the knowledge gaps identified above that have remained unaddressed in existing literature.

3. Methodology

3.1 Fuzzy Analytic Hierarchy Process (FAHP)

The Analytic Hierarchy Process (AHP) was first introduced by Saaty (Saaty, 1980) and has become a widely adopted approach for weighting dissimilar performance measures in multi-criteria decision-making (MCDM) challenges across fields such as engineering, economics, and supply chain management. The AHP method helps to quantify the weights of criteria using the judgment of domain experts for complex decision-making problems. However, because AHP uses crisp numerical values to represent these human judgments, it fails to accurately capture the uncertainty and ambiguity in evaluations. This limitation may lead to inaccurate assessments by overlooking the vagueness present when mapping qualitative judgments to quantitative weights (Sipahi & Timor, 2010; Vaidya & Kumar, 2006). This risk of inaccurate judgment, resulting from human biases, underscored the need for improved methods that could effectively account for these ambiguities.

To overcome the limitations of AHP, the Fuzzy Analytic Hierarchy Process (FAHP) was developed as an extension of the AHP method using fuzzy logic (Seçme et al., 2009;Chan & Kumar, 2007; Kahraman et al., 2004, 2006; Liu et al., 2020; Weck et al., 1997). Fuzzy logic is a way to calculate "degrees of truth" by using membership functions that capture the uncertainty of human judgments, rather than depending on crisp values (Kubler et al., 2016). As real-world problems are often highly complex, imprecision in human judgments requires approaches like FAHP to account for these judgments properly. For example, in multi-dimensional performance assessment, human judgments about the significance of factors across different domains are uncertain, requiring approaches like FAHP to capture such ambiguity effectively. This research employs the FAHP method proposed by Chang (Chang, 1996), a widely used approach that utilizes triangular membership functions to intuitively represent human judgements and efficiently process data without extensive computational complexity (Wang & Tong, 2016). A detailed description of the FAHP method and its equations is provided in Supplementary Information.

3.2 Life Cycle Performance Indicator (LCPI)

Building on the FAHP methodology described in the previous section, the Life Cycle Performance Indicator (LCPI) integrates the calculated factor weights into a single indicator that quantifies performance throughout the product's life cycle. The following seven steps outline the procedures used to compute the LCPI in this study, which are summarized schematically in Figure 3.

- Step 1: Define problem
- Step 2: Build hierarchical structure
- Step 3: Collect data
- Step 4: Construct fuzzy pairwise matrix
- Step 5: Calculate weights
- Step 6: Compute LCPI
- Step 7: Decision making

Step 1: The first step in calculating the LCPI is to define the decision-making problem and set the overarching goal. Following this, relevant criteria, sub-criteria, and individual indicators are organized to reflect the multi-dimensional aspect of overall life cycle performance.

Step 2: A hierarchical structure is established, with the goal at the highest level, followed by criteria, sub-criteria, individual indicators and alternatives in descending order.

Step 3: To determine the relative importance among the elements (criteria, sub-criteria, and individual indicators) in the hierarchical structure, experts were asked to perform pairwise comparisons using a predefined set of linguistic terms. These terms express varying degrees of relative significance, such as equally important, moderately more important, or extremely more important, allowing experts to convey their judgments. Each expert completed questionnaires that included all necessary pairwise comparisons relevant to the hierarchy. To ensure the reliability of the responses collected, a panel of experts was selected based on their professional experience and domain expertise. In parallel with the expert judgment collection, data for the individual indicators under the economic efficiency, pollutant release level, and workforce stability criteria are gathered for each stage of the product life cycle from sources including literature reviews, government databases, and corporate reports. These data subsequently serve as inputs for the LCPI calculation in Step 6.

Step 4: The collected linguistic pairwise comparisons from experts are established in matrix form across all hierarchy levels, with each entry indicating the relative importance of one criterion over another. These entries are then converted into their corresponding triangular fuzzy number (TFNs) as shown in Table 1, and assigned to the upper triangle of the matrix, while the lower triangle is automatically filled using the triangular fuzzy reciprocal scale. A triangular fuzzy number (a,b,c) represents the minimum possible value, b the mode value, and c the maximum possible value in comparing two options. The fuzzy scale used in this study follows commonly accepted triangular fuzzy numbers (TFNs) widely applied in FAHP studies (Calabrese et al., 2016; Tseng et al., 2009; J. J. Wang et al., 2008). These TFNs introduce flexibility into the uncertainty of decision-makers' judgments, helping to account for ambiguity in complex decision-making.

Table 1. Triangular fuzzy scale

Linguistic scale	Triangular fuzzy number	Triangular fuzzy reciprocal number
Equally important	(1,1,1)	(1,1,1)
Weakly more important	(1,3/2,2)	(1/2,2/3,1)
Moderately more	(3/2,2,5/2)	(2/5,1/2,2/3)
Strongly more	(2,5/2,3)	(1/3,2/5,1/2)
Extremely more	(5/2,3,7/2)	(2/7,1/3,2/5)

Step 5: Using the fuzzy pairwise comparison matrix, which consists of triangular fuzzy numbers (TFNs), the synthetic extent values are computed. These values serve as intermediate representations of how well each element (criteria, sub-criteria, and individual indicators) satisfies a defined goal in Step 1. Next, the fuzzy synthetic extents of all element pairs are compared to determine the degree of possibility that one is more significant than another. These comparisons yield a set of priority scores, which are then normalized to produce the final weights of the elements. The detailed computational procedures for deriving these weights are provided in Section 3.1.

Step 6: Using the data collected in Step 3 (see Supplementary Information for details), two adjustments were made prior to LCPI calculation. First, since the units of the data collected for the influence factors under the economic efficiency, pollutant release level, and workforce stability criteria vary, we computed the ratio relative to the total for each individual indicator, making it a valid approach for comparing values on a relative scale. Second, recognizing that certain individual indicators have adverse effects on the aim of improving life cycle performance, negative values were assigned to these factors, ensuring their influence is properly reflected in the model. This conditional application of a negative sign distinguishes between positive and negative influences on life cycle performance. The weights obtained from Step 5 were then used to compute the weighted sum of the data for individual indicators under the economic efficiency, pollutant release level, and workforce stability criteria for each life cycle stage, normalized against the maximum and minimum values to yield a dimensionless indicator ranging from 0 to 1 and representing the relative life cycle performance of each stage.

The calculation of LCPI can be structured in equations as follows. Let the collected data be represented as a matrix D, where each row corresponds to product life cycle stages and each column corresponds to individual indicators collected for the analysis. We define $D_{p,i,j}$ as a matrix that captures the elements of the i^{th} product life cycle stage and j^{th} individual indicator under p^{th} criteria. Once the data matrix D is structured, the next step involves computing the ratio for each column within the entire matrix. For each column j, this ratio computation can be expressed as Eq. (1).

$$R_{p,i,j} = \frac{D_{p,i,j}}{\sum_i D_{p,i,j}}, for\ all\ columns\ j \quad (1)$$

After computing the ratios, for influencing factors that have adverse effects on the aim of improving life cycle performance, negative values were assigned to the corresponding columns in the data matrix to reflect their impact, as shown in Eq. (2).

$$M_{p,i,j} = \begin{Bmatrix} -R_{p,i,j}\ only\ for\ variable\ j, where\ j\ is\ defined\ as\ having\ negative\ impact \\ R_{p,i,j}\ otherwise \end{Bmatrix} \quad (2)$$

Using the matrix $M_{p,i,j}$, Life Cycle Performance Indicator (LCPI) value for each product life cycle stage can be calculated by Eq. (3). The calculated results fall within the range of 0 to 1, enabling the assessment of their relative performance across the life cycle stages.

$$LCPI_i = \frac{\sum_p \sum_j M_{p,i,j} W_{p,j} - \min_i \sum_p \sum_j M_{p,i,j} W_{p,j}}{\max_i \sum_p \sum_j M_{p,i,j} W_{p,j} - \min_i \sum_p \sum_j M_{p,i,j} W_{p,j}} \quad (3)$$

$LCPI_i$ is life cycle performance indicator value for i^{th} life cycle stage and w_{pj} is weight of the j^{th} individual indicator under p^{th} criterion. $M_{p,i,j}$ is the data matrix where i is index for the product life cycle stage, j is index for the individual indicator, and p is index for the criteria.

Step 7: Based on the computed LCPI values, life cycle stages showing relatively lower performance can be identified and prioritized for improvement actions. The LCPI serves as a tool for decision-makers to focus their efforts on the life cycle stages most in need of performance improvement.

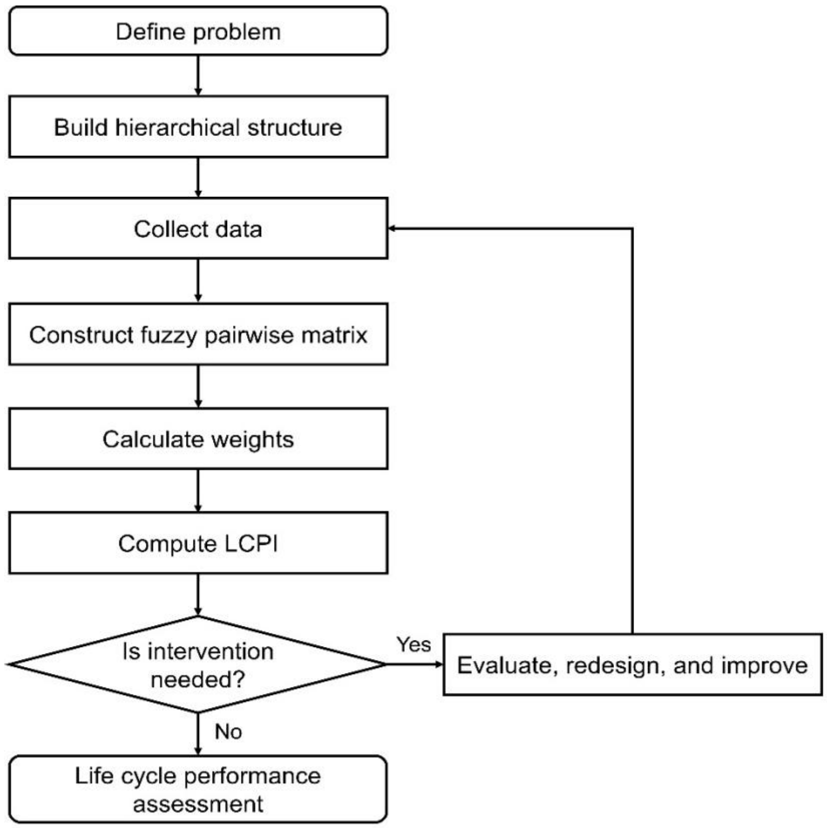

Fig.3. Schematic representation of calculating LCPI

4. Criteria selection and weight calculation

4.1 Criteria, sub-criteria, and individual indicators

This section presents the criteria, sub-criteria, and individual indicators utilized in this study based on rigorous literature reviews, as shown in Table 2 (Azadnia et al., 2015; Chan & Kumar, 2007; Ghadimi et al., 2012; Herva et al., 2011; Ho et al., 2010; Liu et al., 2013; Pohekar & Ramachandran, 2004; Shi et al., 2015; Zimmer et al., 2016). These criteria, sub-criteria, and individual indicators were selected to provide a comprehensive perspective on life cycle performance assessment, integrating diverse aspects of economic efficiency, pollutant release level, and workforce stability. They were then validated through expert consultations to confirm their relevance. By accounting for diverse considerations, this study conducted a thorough analysis that is important in Multi-Criteria Decision Analysis (MCDA), which requires detailed understanding of the relationships between factors (Wang et al., 2009).

The selected criteria, sub-criteria, and individual indicators were organized into a hierarchical structure to assess the life cycle performance, as illustrated in Figure 4. The structure comprises several levels, where each upper-level element is broken down into sub-elements to enable systematic evaluation. This structure clarifies the relationships among the levels considered in the assessment.

Table 2. Selected criteria, sub-criteria and individual indicators

Criteria	Sub-criteria	Individual indicators
Economic efficiency	Purchasing Cost	Cost to buy materials for manufacturing
		Cost to buy materials for remanufacturing
	Operating Cost	Labor cost for manufacturing
		Labor cost for remanufacturing
	Transportation Cost	Material transportation cost
		New diesel engine transportation cost
		Old diesel engine transportation cost
		New LNG engine transportation cost
	Recycling Benefit	Cost benefit from material recycling
Pollutant release level	GWP (Global Warming Potential)	Amount of CO_2
		Amount of CH_4
		Amount of NO_x
		Amount of CO
	AP (Acidification Potential)	Amount of SO_2
		Amount of NO_x
		Amount of H_2S
		Amount of HCL
	EP (Eutrophication Potential)	Amount of NH_4
		Amount of COD
	ODP (Ozone Depletion Potential)	Amount of $CFCs$
	POCP (Photochemical Ozone Creation Potential)	Amount of CO
Workforce stability	Safety and Health	Non-fatal injuries / calendar year
		Amount of SO_2
	Labor Volatility	Long-term labor productivity change
		Long-term unit labor cost change
		Long-term hours worked change
		Long-term labor compensation

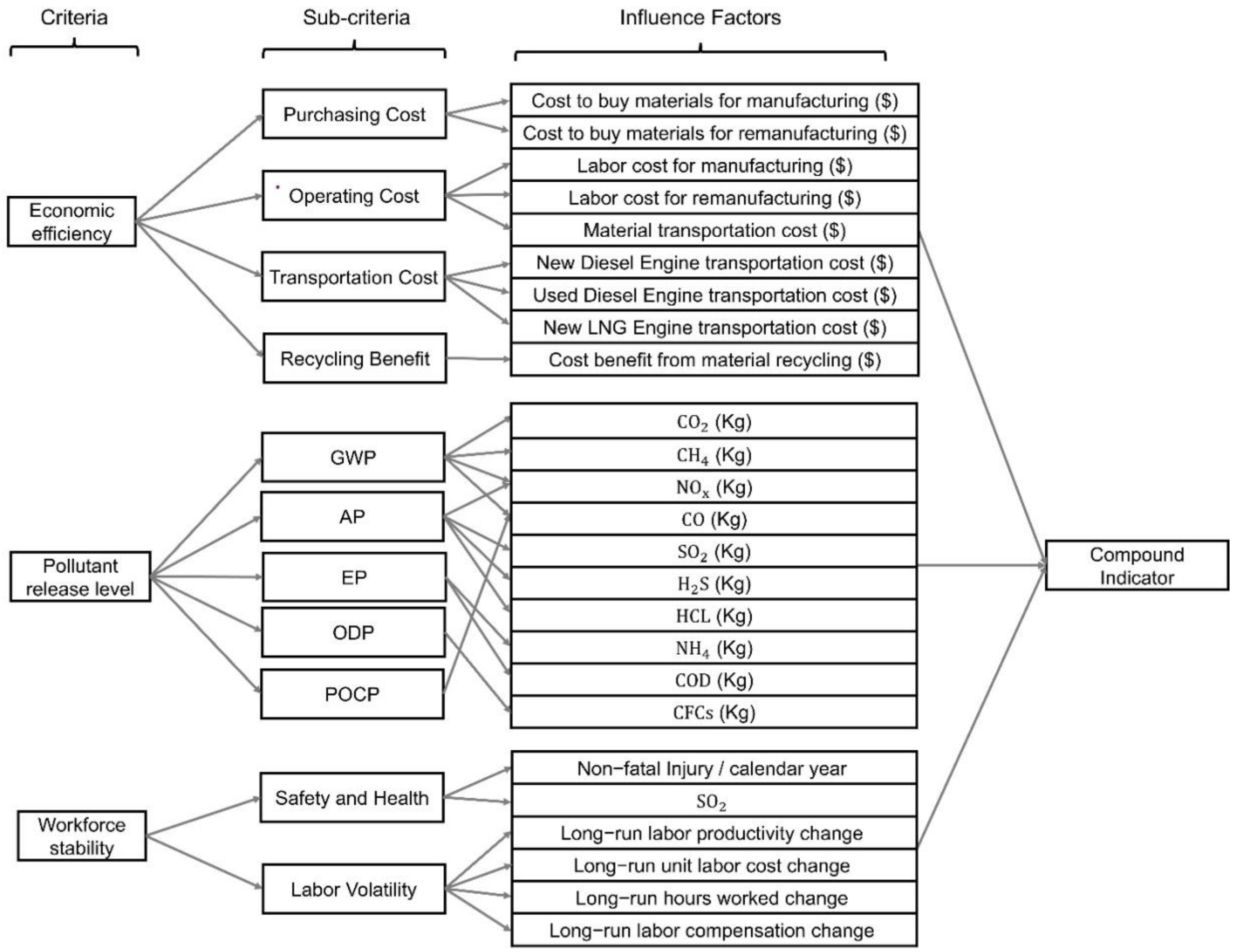

Fig. 4. Hierarchical structure for LCPI calculation (Units: [$/kg] for purchasing cost and recycling benefit; [$/hour] for operating and transportation cost; [$kg\ CO_2$ *eq*], [$kg\ SO_2$ *eq*], [$kg\ NO_3$ *eq*], [$kg\ CFC_{11}$ *eq*], and [$kg\ C_2H_4$ *eq*] for GWP, AP, EP, ODP, and POCP, respectively; [cases/100 workers] for non-fatal injury; [%/year] for labor volatility)

4.2 Weight calculation

The calculated weights are shown in Table 3 which represents the quantified relative importance of each individual indicator under the economic efficiency, pollutant release level, and workforce stability dimensions. These weights are essential for aggregating these three dimensions into a single indicator, ensuring that more significant factors exert proportionally greater influence in the LCPI calculation. Moreover, a scenario-based analysis can be conducted to show how changes in the data for individual indicators under economic efficiency, pollutant release, and workforce stability criteria, particularly those with higher weights can significantly influence overall performance rankings and reveal areas for improvement.

Table 3. Calculated weights for individual indicators

Criteria	Individual indicator	Weight
Economic efficiency	Cost to buy materials for manufacturing	2.18E-01
	Cost to buy materials for remanufacturing	2.04E-01
	Labor cost for manufacturing	1.77E-01
	Labor cost for remanufacturing	1.23E-01
	Material transportation cost	1.15E-01
	Old diesel engine transportation cost	9.54E-02
	Cost benefit from material recycling	3.94E-02
	New diesel engine transportation cost	1.89E-02
	New LNG engine transportation cost	8.57E-03
Pollutant release level	Amount of NO_x	2.08E-01
	Amount of CH_4	1.92E-01
	Amount of CO	1.44E-01
	Amount of CO_2	1.39E-01
	Amount of H_2S	1.24E-01
	Amount of HCL	7.69E-02
	Amount of SO_2	5.95E-02
	Amount of $CFCs$	4.52E-02
	Amount of NH_4	1.03E-02
	Amount of COD	1.35E-03
Workforce stability	Non-fatal injuries / calendar year	3.18E-01
	Long-term labor compensation change	2.46E-01
	Amount of SO_2	1.90E-01
	Long-term labor productivity change	1.45E-01
	Long-term unit labor cost change	8.77E-02
	Long-term hours worked change	1.23E-02

5. Results and analysis

5.1 Case study description

This paper investigates the product life cycle stages of a diesel engine that can be remanufactured into an LNG engine, comprising ten key stages as shown in Figure 5. It begins with “Raw Materials Production,” where the necessary materials for diesel engine production are sourced and created. The next step is "Materials Transportation," which involves moving these materials to the manufacturing facility. "Diesel Engine Manufacturing" follows where the diesel engines are produced. Once manufactured, the diesel engines are transported to their designated locations for “Diesel Engine Transportation” and subsequently used in various applications, constituting the “Diesel Engine Use” phase. After this, "Additional Materials Production" comes to produce materials required to remanufacture end-of-life diesel engines into new LNG engines. Following this, “Old Diesel Engine Transportation” transports EoL diesel engines and these are remanufactured into LNG engines in the "Remanufacturing to LNG Engine" stage. Finally, the newly created LNG engines are transported and put to use, completing the process with "LNG

Engine Transportation" and "LNG Engine Use." This comprehensive process covers the entire lifecycle of diesel and LNG engines, from their material processing, transportation and to their ultimate utilization.

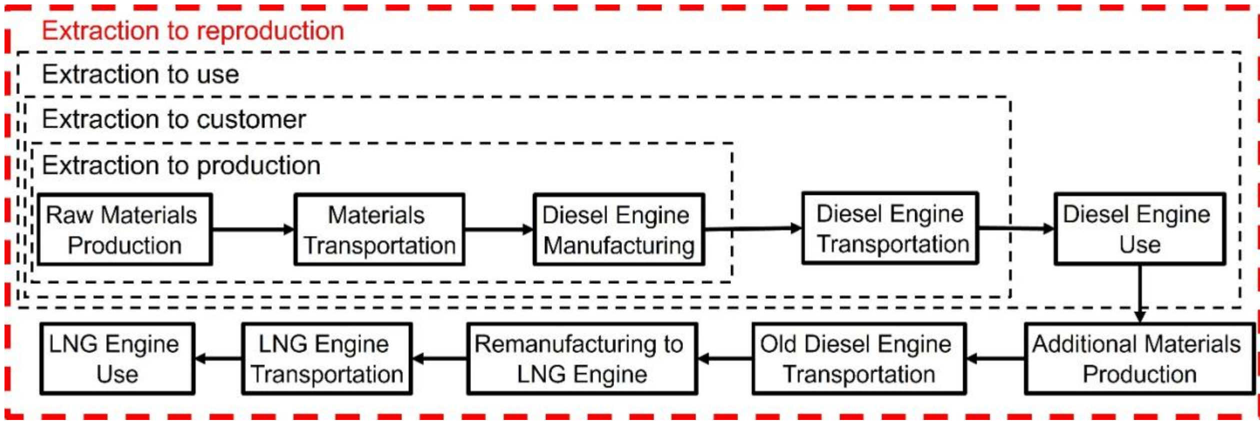

Fig. 5. Selected boundary for analysis

5.2 Life cycle performance evaluation

The relative life cycle performance evaluation can be made based on the LCPI value, as shown in Table 4. A lower LCPI value indicates a stage that needs significant improvement, whereas a higher LCPI value indicates a stage that performs better. This is because the LCPI calculation accounts for whether each individual indicator contributes positively or negatively to overall performance, meaning that indicators with beneficial effects increase the LCPI value, while those with adverse effects lower it. Individual indicators that have negative impacts (e.g., CO_2 discharge) are penalized, leading to lower values, while those with positive impacts (e.g., cost benefit from material recycling) contribute to higher values.

In this case study, both use phases, “Diesel Engine Use” and “LNG Engine Use” were identified as the two most critical stages needing improvement, with LCPI values of 0 and 0.41, respectively. One potential reason for having the lowest LCPI values in both use phases is the high pollutant release levels associated with the use of diesel and LNG engines across almost all pollutant-related factors (see Supplementary Information for details). Conversely, the highest LCPI value is observed during the “LNG Engine Transportation” phase, with a score of 1, indicating that it exhibited the greatest life cycle performance among the evaluated stages. This phase is followed by “Diesel Engine Transportation” and “Additional Materials Production,” which have LCPI values of 0.989 and 0.899, respectively.

Based on the calculated LCPI values, life cycle stages can be further categorized using a quartile method, which divides the values into four groups by ordering them from lowest to highest. These four categories correspond to life cycle stages exhibiting high (4), moderate (3), low (2), and very low (1) performance levels. This categorization provides a simple way to understand the life cycle performance at a glance, even for individuals unfamiliar with LCPI values. It simplifies communication and supports quick identification of stages that require greater focus to improve the overall life cycle performance.

Table 4. Life cycle performance analysis

Life cycle stage	LCPI value	Categorization
Raw Materials Production	0.854	3
Materials Transportation	0.847	2
Diesel Engine Manufacturing	0.553	2
Diesel Engine Transportation	0.989	4
Diesel Engine Use	0	1
Additional Materials Production	0.899	3
Old Diesel Engine Transportation	0.872	3
Remanufacturing to LNG Engine	0.603	2
LNG Engine Transportation	1	4
LNG Engine Use	0.452	1

5.3 Scenario analysis

Considering that the data collected for each dimension can be affected by potential changes such as economic trend shifts, stricter technical standards, and evolving labor conditions, it is necessary to assess how the LCPI value responds to these variations through a scenario-based simulation analysis. Such an approach facilitates assessment of the collective impact of these pillars on the LCPI value and supports the identification of targeted improvement actions through an understanding of trade-offs among them. These insights are vital for making informed decisions that align with corporate objectives and industry requirements.

The examination was conducted to thoroughly evaluate changes in the average LCPI values across all ten life cycle stages and to assess how economic efficiency, pollutant release level, and workforce stability collectively influence the LCPI value under various data scenarios. The rationale behind undertaking this analysis arises from the growing acknowledgment of the interconnectedness among these dimensions when assessing life cycle performance. This facilitates an evaluation that goes beyond traditional single-factor assessments, providing a detailed understanding of how variations in economic efficiency, pollutant release level, and workforce stability factors jointly affect the LCPI value.

We adjusted the data collected for the economic efficiency, pollutant release level, and workforce stability dimensions (see Supplementary Information for details) from -100% to +100% of its nominal value in 5% increments. For example, the amount of CO_2 release amount during "Raw Materials Production" stage ($2.73 * 10^3\ kg\ CO_2eq$) was modified to assess how both reductions and increases in this value would affect the LCPI. The same percentage adjustment was applied to all individual indicator values within each dimension. This means that, for example, if a -10% change is applied to the economic efficiency dimension, all associated indicator values are adjusted by -10%. We then analyzed how these variations affect the LCPI value based on all combinations.

The result is shown in Figure 6, which provides a comprehensive visualization of how changes in economic efficiency, pollutant release, and workforce stability dimensions affect the LCPI values. This figure enables the identification of relationships between the three dimensions and the existence of optimal zones, highlighted as the blue region, where the most preferred scenarios are found. The mixed coloration in the figure shows trade-offs, where improvements in some dimensions can lead to setbacks in others. Consequently, achieving higher LCPI value requires a balance among economic efficiency, pollutant release level, and workforce stability dimensions, as neglecting any one dimension could lead to lower overall life cycle performance. Extreme values in any single dimension do not necessarily result in higher outcomes, indicating that a single-minded focus on only one aspect is insufficient.

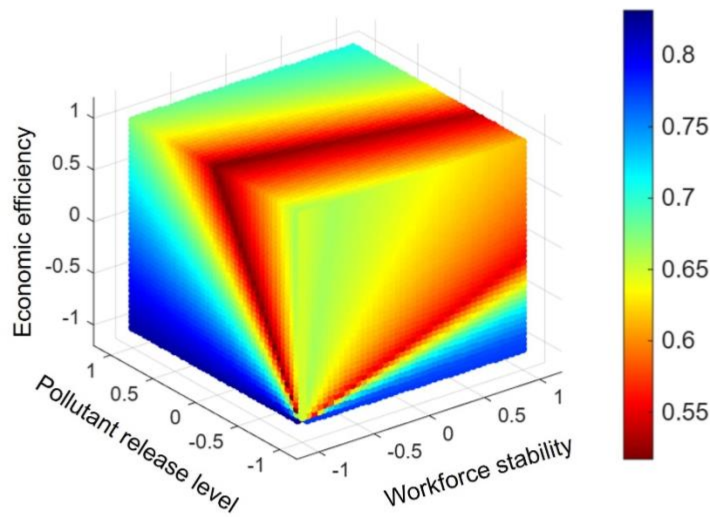

Fig. 6. LCPI values across all three dimensions

The impact of variations in two dimensions on the LCPI values is examined and illustrated in the three plots presented in Figure 7. First, Figure 7 (a) shows how average LCPI values change based on variations in the data for individual indicators under the economic efficiency and pollutant release level criteria. The figure shows that the average LCPI values are highly sensitive to both economic efficiency and pollutant release level changes. As these dimensions vary, the average LCPI values also change significantly, which suggests that both economic efficiency and pollutant release level factors are crucial in influencing overall life cycle performance.

Second, Figure 7 (b) illustrates how average LCPI values change based on variations in the data for individual indicators under the pollutant release level and workforce stability criteria. As data points move in the negative direction along the economic efficiency axis, indicating lower economic costs, and in the positive direction along the workforce stability axis, indicating improved workforce stability, blue regions are observed, signifying an increase in overall life cycle performance. In contrast, as data points move in the positive direction along the economic efficiency axis and in the negative direction along the workforce stability axis, red regions are observed, signifying a decrease in overall life cycle performance. The figure shows that the average LCPI values are less sensitive to changes in the economic efficiency-workforce stability dimensions compared to the economic efficiency-pollutant release level combination.

Third, Figure 7 (c) depicts how average LCPI values change based on variations in the data for individual indicators under the pollutant release level and workforce stability criteria. The plot shows a gradual transition from red to blue, indicating a slow change in life cycle performance rather than abrupt shifts. One interesting fact observable in the plot was that at a certain point, the LCPI value hit its lowest point and then began to rise again. This trend suggests the presence of critical tipping points where life cycle performance can significantly decline if pollutant release level and workforce stability dimensions are not adequately managed. However, it also indicates the potential for a rebound in life cycle performance, emphasizing the importance of careful adjustments in pollutant release level and workforce stability dimensions.

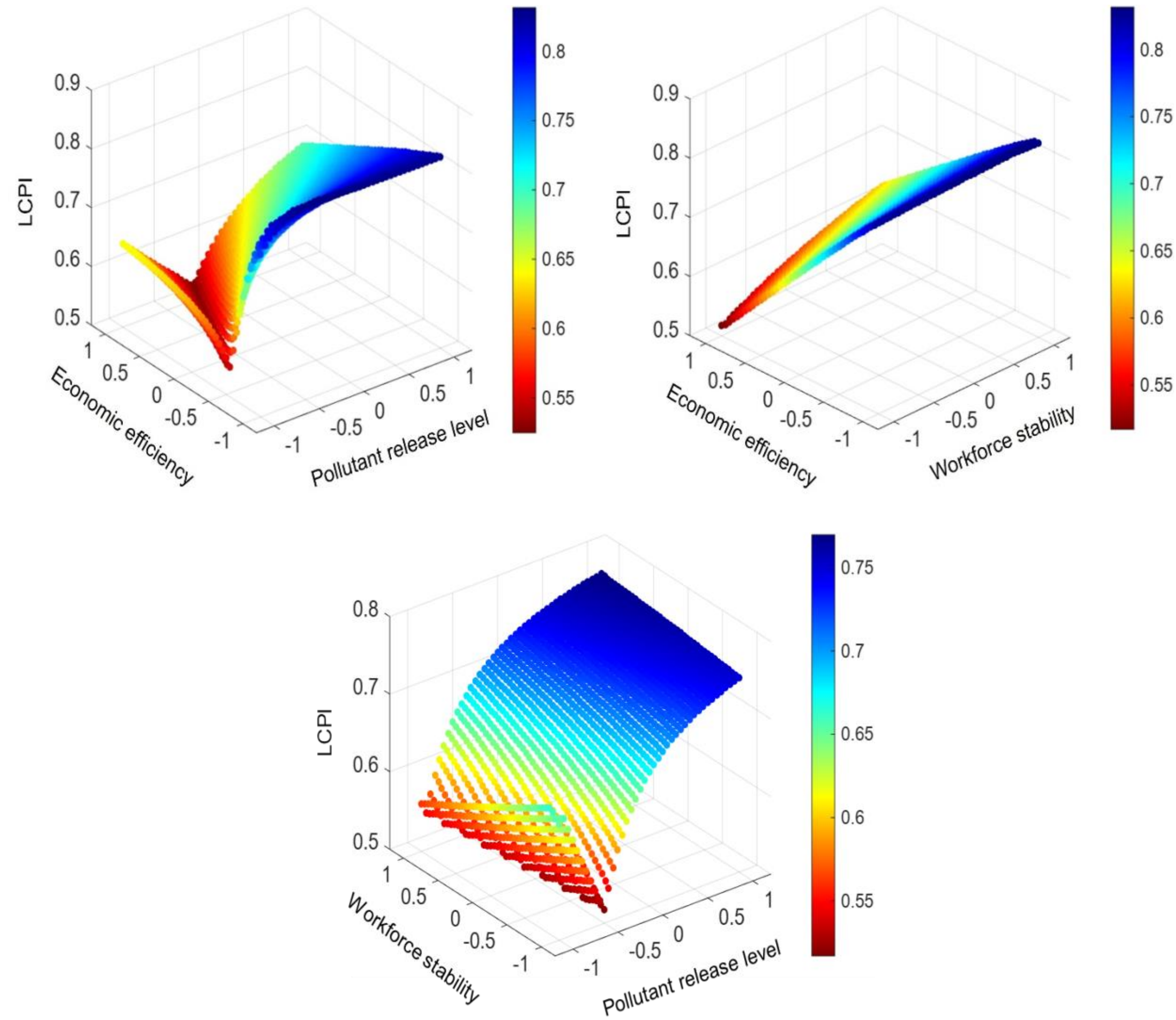

Fig. 7. LCPI values under variation in two dimensions

5.4 Simulation results

The simulated improvements in LCPI under different data variation scenarios across the economic efficiency, pollutant release level, and workforce stability dimensions are summarized in Table 5. Data adjustments ranging from -10% to +10%, extending to -100% to +100% in 5% increments are analyzed to understand the effects under different cases. These ranges are grouped into ten scenarios, with scenario 1 covering -10% to +10%, scenario 2 from -20% to +20%, and so forth, up to scenario 10, which includes -100% to +100%. The variation from -100% to +100% was selected to investigate the wide spectrum of changes in economic efficiency, pollutant release level, and workforce stability, allowing decision-makers to prepare for diverse future conditions that may impact life cycle performance. This approach generates a wide range of data combinations for analyzing the combined influence of economic efficiency, pollutant release level, and workforce stability variations on LCPI outcomes. Additionally, the minimum and maximum LCPI values for each scenario are provided, capturing the full spectrum of outcomes across all data combinations (see Supplementary Information for detailed simulation results).

The results indicate a clear trend in which simulated LCPI improvements increase as the data is varied more extensively across all tested combinations. Among the tested combinations, varying the data across all three dimensions produces the highest simulated life cycle performance improvement of 60.85%, with LCPI values increasing from 0.5170 to 0.8316. When the data for economic efficiency and workforce stability is varied, the simulated improvement reaches 60.84%, with values increasing from 0.5170 to 0.8315. Varying the data for economic efficiency and pollutant release level results in an improvement of 58.42%, increasing from 0.5248 to 0.8314. Lastly, varying the data for pollutant release level and workforce stability produces the smallest improvement of 48.88%, with values increasing from 0.5170 to 0.7697, indicating a lesser impact on simulated LCPI improvement compared to the previous two cases. This indicates that the economic efficiency dimension has a greater influence on changes in the LCPI value compared to the pollutant release level and workforce stability dimension.

The findings indicate that varying all three dimensions presents the greatest simulated LCPI improvement, with economic efficiency and pollutant release level combinations showing the next strongest effect. This suggests that multi-dimensional life cycle initiatives may yield more substantial performance gains than focusing solely on one or two pillars. At the same time, the findings show that beyond a certain threshold, further data variations yield diminishing returns, emphasizing the importance of careful and targeted interventions in each pillar. This insight can support decision-makers in identifying which combinations of data adjustments are most likely to yield substantial improvements, especially when decisions must be made under constrained conditions.

Table 5. Summary of simulation results for LCPI value

Criteria combinations	Min LCPI value	Max LCPI value	Scenario-based LCPI Change Range (%)
Economic efficiency, Pollutant release level, and Workforce stability	0.5170	0.8316	60.85
Economic efficiency and Pollutant release level	0.5248	0.8314	58.42
Economic efficiency and Workforce stability	0.5170	0.8315	60.84
Pollutant release level and Workforce stability	0.5170	0.7697	48.88

A major aspect to consider is the point at which life cycle performance enhancement starts to plateau, signaling a decline in the rate of further performance gains. Figure 8 visualizes the simulated improvements in LCPI across various combinations of life cycle dimensions, identifying where they begin to yield diminishing returns. A threshold line is drawn on each plot, indicating the point at which further data variation does not result in a steep increase in LCPI improvement; beyond this threshold, improvements become more gradual.

When variations occur in economic efficiency, pollutant release level, and workforce stability, it is clear that the LCPI improvement increases steeply as the data variation rises from scenario 1 to scenario 5. Beyond this point, the rate of increase in LCPI improvement begins to level off, suggesting diminishing returns on life cycle improvements with further data variation. This implies that efforts to improve data in all three pillars can result in substantial gains, but beyond a certain point, it becomes less responsive to further changes. Similarly, the economic efficiency and pollutant release level data variation case, as well as the economic efficiency and workforce stability data variation case, demonstrate the same pattern of diminishing returns on life cycle performance improvements. However, the pollutant release level and workforce stability data variation case reveals a slightly different pattern with a less steep initial increase but a more consistent continuous climb. This suggests that the interplay between the pollutant release level and workforce stability dimensions is less sensitive to minor data variations but remains steadily influential even with broader variation intervals.

The analysis shows simulated improvements in life cycle performance and identifies threshold points beyond which further efforts become less effective. This knowledge can guide decision-makers in determining where and how to focus their efforts to enhance their performance efficiently. These thresholds vary depending on which pillars are being adjusted, indicating that a deliberate approach is necessary to achieve desired outcomes.

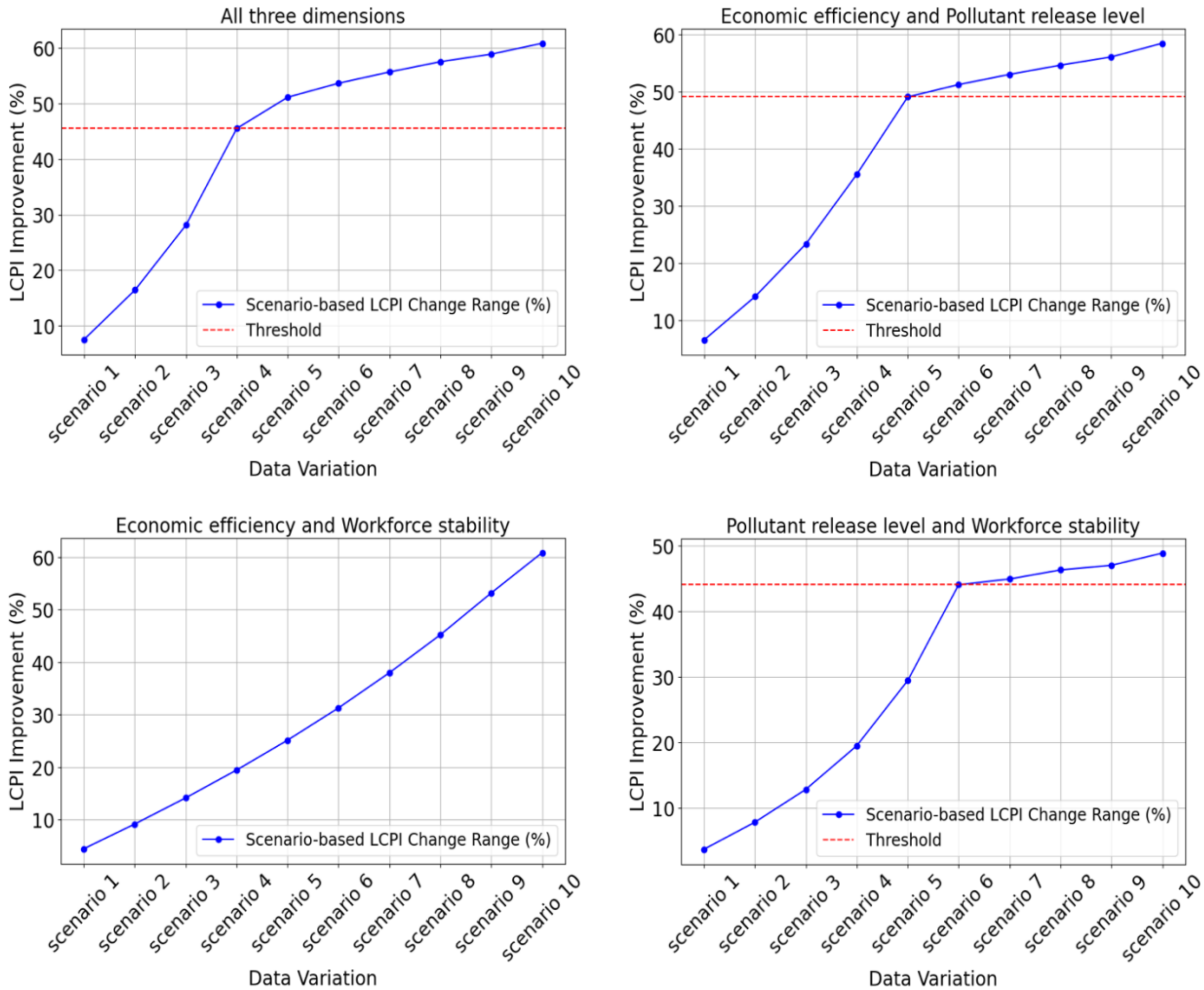

Fig. 8. LCPI improvement trends across various dimensions

6. Conclusion

This study developed a new indicator, the Life Cycle Performance Indicator (LCPI), which integrates multi-dimensional aspects (economic efficiency, pollutant release level, and workforce stability) into a single measure to provide a holistic evaluation of each product life cycle stage. In the calculation of LCPI, the Fuzzy Analytic Hierarchy Process (FAHP) method was utilized to determine the weights among various criteria when uncertainties are inherent in complex decision-making. A case study of a diesel engine remanufactured into an LNG engine was conducted to illustrate how the proposed indicator can be used for life cycle performance assessments. Insights drawn from LCPI values point to specific stages with comparatively low life cycle performance, offering clear guidance on where to focus improvement initiatives.

The scenario-based analysis results show the collective influence of economic efficiency, pollutant release level, and workforce stability on the LCPI value, emphasizing their interconnectedness and the balance required among all dimensions to enhance overall performance. By analyzing variations in LCPI values across different data scenarios, this study identifies cases with substantial simulated improvements in LCPI outcomes. The results suggest that an improvement of up to 60% in life cycle performance can be observed when all three dimensions are well-adjusted in the evaluated scenarios. However, our analysis also shows that the rate of improvement starts to plateau, meaning that additional changes yield diminishing returns beyond certain thresholds. This points to the importance of implementing well-considered changes within each pillar to achieve greater performance.

The Life Cycle Performance Indicator (LCPI) serves as a practical tool for evaluating performance at each life cycle stage, providing insights that support decision-making where detailed assessments are required. This research lays the foundation for future efforts to build indicators that assess life cycle performance at a granular level. For future directions, additional factors can be incorporated to understand how the intricacies among these factors influence the LCPI value, thereby depicting real-world scenarios more accurately. Moreover, the indicator proposed in this research can be further modified to a wider range of sectors or more complex product life cycle scenarios, depending on the available data and individuals' fields of interest. Lastly, it is important to acknowledge contingent events (e.g., the Russian invasion of Ukraine) that could influence the material price assumptions used in this study.

CRediT authorship contribution statement

Yong Han Kim: Conceptualization, Methodology, Analysis, Software, Writing - original draft. Sidi Deng: Validation, Writing - review & editing. Thomas Maani: Validation, Writing - review & editing. Matthew J. Triebe: Validation, Writing - review & editing. Nehika Mathur: Validation, Writing - review & editing, Project administration. John W. Sutherland: Writing - review & editing, Project administration, Funding acquisition, Supervision.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data Availability

Data will be made available on request.

Acknowledgments

The authors gratefully acknowledge the support from: i) the National Institute of Standards and Technology (NIST) [Grant Number 70NANB22H105]; ii) the Critical Materials Innovation (CMI) Hub led by Ames National Laboratory [Contract No. DE-AC02-07CH11358]; and iii) The Climate Imperative Foundation. Special thanks to the industry advisors on the NIST project for providing expert opinions as part of the FAHP process.

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