Journal of Management and Sustainability; Vol. 13, No. 2; 2023
ISSN 1925-4725 E-ISSN 1925-4733
Published by Canadian Center of Science and Education

Optimization in Life Cycle Sustainability Assessment (LCSA): A Systematic Literature Review

Julianna Crippa[1] & Cassia Maria Lie Ugaya[1]

[1] Federal University of Technology, Paraná, Brazil

Correspondence: Julianna Crippa, St. Dep. Heitor Alencar Furtado, number 5000, Curitiba/PR, Postal Code 81280-340, Brazil.

Received: February 3, 2023 Accepted: June 25, 2023 Online Published: July 19, 2023

doi:10.5539/jms.v13n2p68 URL: https://doi.org/10.5539/jms.v13n2p68

Abstract

This secondary scientific research follows the modality of review research through the systematic literature review (SLR) technique and aims to answer the following question: What methods in the literature use optimization techniques to develop Life Cycle Sustainability Assessment (LCSA)? The objective is to identify and map information, relate their applications, and provide a critical analysis. The research was conducted in a global context, on April 2, 2022, with no time horizon limit, in English, using Harzing's Publish or Perish tool and search sources: Scopus®, Web of Science™, and Google Scholar. After the automatic exclusion of duplicate titles, the selection of articles was carried out in five further steps: first filtering, second filtering, third filtering, fourth filtering, and finally the snowball system. Regarding the years of selected publications, a slow but continuous upward trend (growth) can be seen. A diversity of journals can be observed and that most methods integrating optimization and LCSA focus on each product/system or application. Each optimization model proposal has its specific characteristics when combined with LCSA. Overall, there is a greater frequency of articles that propose to evaluate by comparing alternative products/supply chains/production processes, followed by those that use optimization for product development in selecting the best design from a set of alternatives. This research confirms that Operational Research (OR) operates in different segments and can use different techniques to obtain optimal solutions and decision support. The optimization techniques found in this or other literature reviews should be evaluated against an established analytical model by applying them to the same case study.

Keywords: decision making, social, environmental, costing, LCSA, E-LCA, S-LCA, LCC, sustainable, optimization, mathematical models, algorithms, optimal solution

1. Background and Concepts

The integrated Life Cycle Sustainability Assessment (LCSA) tool designed by Kloepffer (2008) and based on the principles of the “triple bottom line” has been widely used (COSTA; QUINTEIRO; DIAS, 2019). The publication Towards a Life Cycle Sustainability Assessment (UNEP/SETAC, 2011) emphasizes that LCSA enables professionals and companies to assess the impacts of their purchasing decisions and production methods. Companies and researchers can apply it to different aspects of the value chain, which can directly or indirectly affect the consumer's choice preference for the product. Kloepffer (2008) schematizes LCSA as a compilation of Life Cycle Assessment (LCA or E-LCA), Life Cycle Costing (LCC), and Social Life Cycle Assessment (S-LCA). An LCA examines the potential environmental impacts over the entire life cycle of a product or system, taking into account the results of resource extraction, transportation, production, use, recycling, and disposal of products. An LCC is used to quantify the economic aspects and assess the life cycle cost impacts. In addition, S-LCA assesses social impacts (UNEP/SETAC, 2011). However, the literature review conducted by Costa, Quinteiro, and Dias (2019) shows that there is still no definition in the scientific community on which is the best technique to integrate these three tools (E-LCA, S-LCA, LCC).

Operations Research (OR) is another interdisciplinary area that should be included in the topic. Therefore, it is necessary to go back in the timeline to 1939 in Great Britain. An entry in the Encyclopedia Britannica (Eilon et al., 2018) states that due to limitations in the use of radar to control enemy attacks during World War II, there was a need to test a scientific interdisciplinary systemic application, now known as Operations Research, under operational conditions. At that time, this scientific application was validated and strategically disseminated in the

United Kingdom and other countries. However, it was not until the 1950s, with the advent of the computer, that OR became widespread in academia as a non-military and more industry-oriented application discipline as we know it today (Note 1).

Bringing this area of research up to date, Eom and Kim (2006) show that in the application of operations research to decision support systems, the methods that dominate more than half of the scientific literature are of the type that involve optimization techniques. Optimization has become an essential component in a wide variety of manufacturing sectors and in many cases is a critical factor in the project development process. However, this task is usually complex and involves the manipulation of available design parameters to find good values for one or more objectives, which are evaluated through elaborate computer simulations and depend on numerous constraints that must be satisfied in the optimization process. These methods usually facilitate decision making for complex problems in different areas of engineering projects (Yang & Koziel, 2013).

Although there is no consensus among authors, optimization procedures can be categorized according to their dynamics: 1) deterministic, such as Linear Programming models, Goal Programming, Integer Programming, Nonlinear Programming, Dynamic Deterministic Programming, Network Optimization (via Mixed Integer Linear Programming or Graph Theory), Transportation Logistics Model, and others; 2) stochastic, belonging to this group are Simulation (heuristic methods or based on discrete events), Queue Theory, Game Theory, Dynamic Stochastic Programming (Markov), and others; and, 3) other techniques, such as Machine Learning technique, among others (Belfiore & Favero, 2013; Eom & Kim, 2006; Golbarg & Luna, 2000). It is worth mentioning that the classification of the dynamics of the model depends on the number of variables that compose it. The smaller the number of variables, the more deterministic the dynamics of the process, and the larger the number, the more indeterminate (Golbarg & Luna, 2000). Thus, when using a deterministic model, it is easier to deal with uncertainties because there are few variables. Therefore, this is one of the advantages, because it ensures a higher reliability of the optimal solution(s).

On the other hand, studies such as Eom and Kim (2006) have aimed to provide literature reviews on Operations Research approaches to support decision making in different domains and applications (Ho, Xu, & Dey, 2010; Pohekar & Ramachandran, 2004; Thies et al., 2019; Visentim et al., 2020). Therefore, the techniques studied include not only Multiobjective Decision Making (MODM) (Note 2), but also Multi-Attribute Decision Making (MADM) and methods for evaluating, improving, or measuring efficiency, such as Data Envelopment Analysis (DEA) (Thies et al., 2019). Some examples of MADM methods include Analytic Hierarchy Process (AHP), Analytic Network Process (ANP), Multi-Attribute Utility Theory (MAUT), and Fuzzy Set Theory. It is also worth noting that some studies propose the integrated use of these approaches with each other and with the other optimization techniques mentioned.

To apply this discussion directly to the field of Life Cycle Sustainability Assessment, according to Visentin et al. (2020), it was not until 2013 that the first study integrating some decision support techniques with LCSA was published. The method included MADM by using AHP technique to aggregate the results of LCSA. However, this review did not address the use of Operations Researchoperations research as a way to optimize systems (such as the use of MODM techniques). On the other hand, the authors who published this review emphasized the complexity of many methods that propose to integrate LCSA results for decision making. Since there is no standardized procedure that specifies how this aggregation should be done, there is an increasing need to investigate and develop new methods by applying them in case studies (Visentin et al., 2020).

In reviewing studies that have applied Operations Research to LSCA, Thies et al. (2019) identified three patterns of goals for this integration:

1) To enable LCSA, useful in some cases, i.e., OR application of techniques at certain stages, such as in inventory, impact and allocation calculation, or weighting.

2) To complement LCSA, very commonly used; thus, the assessment results become input values in an optimization method aimed at supporting decision making before, during or after interpretation or for aggregation of indicators.

3) As a substitute for LCSA, a minority of studies that propose to use OR for simplified sustainability assessments, ranging from classifications based on expert judgment to more robust life cycle analyzes.

It is also noteworthy that most articles use technology with a focus on decision making, whether comparing product alternatives, selecting alternatives for project design, or designing an optimal product, among other scenarios. These authors advocated the use of OR methods to enable or complement LCSA (Thies et al., 2019).

In addition, the authors divided the optimization techniques into four more specific categories:

1) Multi-Attribute Decision Making (MADM) methods, which are applied to evaluate a finite set of alternatives based on multiple criteria (attributes, including subjective ones).

2) Multi-Objective Decision-Making (MODM) methods enable the identification and evaluation of Pareto-optimal solutions on the efficiency frontier of a mathematically constrained solution space.

3) Data Envelopment Analysis (DEA) helps to analyze the relative efficiency of a sample of alternatives when the efficient frontier is not known; finally,

4) methods that do not belong to the other three groups mentioned. Moreover, DEA is a linear programming-based technique. However, in the elaboration of the model, a sufficient average number of variables can be assigned, so that it belongs to the group of deterministic models.

The results of Thies et al. (2019) confirm that, as of December 2017, no article was found that addressed the three dimensions of sustainability and used MODM techniques or other techniques (heuristics, artificial intelligence, machine learning, etc.) for decision making. In all cases where the three dimensions were aggregated, MADM techniques were used, and in two rare cases DEA. However, some use of MODM or other techniques for two or one dimension can already be seen.

Combined with the time gap since the publication of the study by Thies et al. (2019)—December 2017 to March 2022—the main objective of this paper is to systematically identify the methods proposed in the literature that use optimization techniques for LSCA. Then, their applications will be analyzed and related.

2. Methodology

This paper aims to answer the following questions: what methods in the literature use OR optimization techniques to develop LCSA? The main goal is then to identify/ map these methods to gather information, relate their applications and develop a critical analysis.

Therefore, this study is classified as secondary scientific research conducted using the systematic literature review (SLR) method. For this purpose, a protocol for SLR was defined, following the scheme proposed by Dresch, Lacerda and Antunes (2015), as shown in Table 1. It is noteworthy that the review was conducted in a global context on April 2, 2022—with no time horizon—in English. Moreover, since the review aims to find primary studies on the topic to obtain the result, it is a review of the aggregative strategy. As for the search terms, search sources, search tools, and article exclusion criteria, these are discussed in more detail in subsection 2.2 (Article Selection).

Table 1. Systematic Literature Review (SLR) protocol

Conceptual *framework*	Optimization methods using OR techniques in LCSA	
Context	Global	
Horizon	All until April 2, 2022.	
Languages	English	
Review Questions	What methods are present in the literature that use OR techniques in LCSA?	
Review Strategy	Aggregative (searches only primary source studies, excludes reviews, for example)	
Search Terms	1. optimization AND life cycle sustainability assessment 2. optimization AND LCSA 3. optimisation AND life cycle sustainability assessment 4. optimisation AND LCSA 5. optimal AND “life cycle sustainability assessment” 6. optimal AND LCSA 7. “operations research” AND “life cycle sustainability assessment” 8. “operations research” AND LCSA 9. “operational research” AND “life cycle sustainability assessment” 10. “operational research” AND LCSA 11. “machine learning” AND “life cycle sustainability assessment” 12. “machine learning” AND LCSA	
Search Sources	Scopus® and Web of Science™ (title, abstract and keywords); Google Scholar (title only).	
Search Tools	Harzing's Publish or Perish - Version 8.2 and CAPES's CAFE Periodical Portal (Web of Science™)	
Exclusion Criteria	**1st Filtering (Reading the titles)**	• Duplicated publication, which the automatic filtering did not identify. • It addresses only one dimension of LCSA (environmental, social, or costing). • It addresses other major themes that escape the main theme.
	2nd Filtering (Reading of the abstracts) Focus on the goal	• Duplicated publication that had not been identified. • It does not deal with optimization methods or Operations Research. • It does not encompass the entire LCSA, it only deals with one or two dimensions. • It is not an article, it is an introduction to conference proceedings or a book - compilations of articles, dissertations. • Secondary scientific research, such as literature review. • It addresses another type of sustainability assessment, not life cycle. • It addresses other major themes that escape the main theme. • Service unavailable in electronic media.
	3rd Filtering (Dynamic reading) Method Focus	• It is not available in English or Portuguese. • It is book, dissertation, or thesis. • It addresses other major themes that escape the main theme.
	4th Filtering (Full Reading) Final check	• Access unavailable. • Articles that had proposed a coherent method, but did not apply it, and therefore there is no validation of the method. • Articles that included all three dimensions of sustainability in their LCSA optimization model, but for some reason when they went to apply it only considered indicators from one or two dimensions.
	Snowball (Full Reading)	• No articles were added that used Operations Research for decision making using only MADM type methods, and such as weighted average, AHP, *Fuzzy sets theory,* etc.

Source: Based on the model of Dresch, Lacerda, Antunes (2015).

2.1 Tools

To automate the operational process of the SLR, we chose the Publish or Perish tool (Harzing, 2007), which has been available to the Society free of charge since 2006. This software allows direct access to and analysis of academic citations from various sources such as Scopus®, Web of Science™, Google Scholar, and Crossref.

First, in a round of testing on October 7, 2021, the tool was reviewed in version 7 (released in 2019). Then, articles were collected by searching four different sources for the search terms in the title, keywords, and abstract: Scopus®, Web of Science™, Google Scholar (the only source where the search is performed in the title only), and Microsoft Academic. With UTFPR institutional access, the researcher could directly access all of these sources through the Publish or Perish tool, with the exception of Web of Science™. Therefore, searches of the

Web of Science™ database had to be performed "manually" through the CAPES journal portal. Subsequently, the results were extracted in RIS file format and imported into the Publish or Perish tool. This solution was only sufficient to include the documents in the platform. However, all citation analysis information (h-index and number of citations) and other incidental information was lost. As mentioned earlier, the last search was performed on April 2, 2022. However, with the release of the new version 8 of the tool, the Microsoft Academic data source was deleted, so its use was no longer possible. In the administration of the publish- or-perish tool, there were errors in the direct import of data from Web of Science™ and Microsoft Academic, missing data in the RIS file imported from Web of Science™, searching for the 12 search terms, searching in Google Scholar performed only by title, and other problems.

In addition, more clarity should be provided on the problems found in the citation data. In the searches, the same article came from different sources, and the citation analysis information needed to be more consistent. For example, the information from Google Scholar usually has a much higher number of citations than that from Scopus®, which has strict scientific criteria to consider. In the test phase, this conflict was not detected. Together with the information lost in the articles imported from the Web of Science™, all the results found were taken into account in the article selection phase, regardless of the number of citations of the individual publications.

At the end of the Publish or Perish tool search, the results were exported to a supporting Google Spreadsheet to eliminate duplicate publications and select articles according to the steps and criteria previously established.

2.2 Article Selection

When exporting the data from the Publish or Perish tool to the supporting spreadsheet, the first step was to exclude duplicate articles. Initially, we excluded duplicate titles found in the data source search with the same term (5th column of Table 2) because we wanted to screen each result separately first. However, the number of duplicate articles was very large, so all articles were combined into a single spreadsheet and all duplicate titles were excluded using an automatic function of the tool. After this exclusion, 86 publications remained (6th column in Table 2), which were analyzed according to the structure of the LSR process shown in Figure 1.

Table 2. Initial results in the search sources and after exclusion of duplicated titles

Search Terms	**Web of Science**	**Google Scholar**	**Scopus**	**Excluding repeats from search terms**	**Excluding all duplicates**
1.optimization AND "life cycle sustainability assessment";	28	9	20	43	**86**
2.optimization AND LCSA;	22	2	23	32	
3.optimisation AND "life cycle sustainability assessment";	3	1	23	25	
4.optimisation AND LCSA;	3	0	23	26	
5.optimal AND "life cycle sustainability assessment";	11	3	12	16	
6.optimal AND LCSA;	13	0	16	18	
7. "operations research" AND "life cycle sustainability assessment";	1	0	3	3	
8. operations research AND LCSA;	1	0	2	3	
9. "operational research" AND "life cycle sustainability assessment";	2	0	2	3	
10. operational research AND LCSA;	0	0	2	2	
11. "machine learning" AND "life cycle sustainability assessment";	1	0	5	5	
12. machine learning AND LCSA;	0	2	3	3	
	82	**17**	**134**		

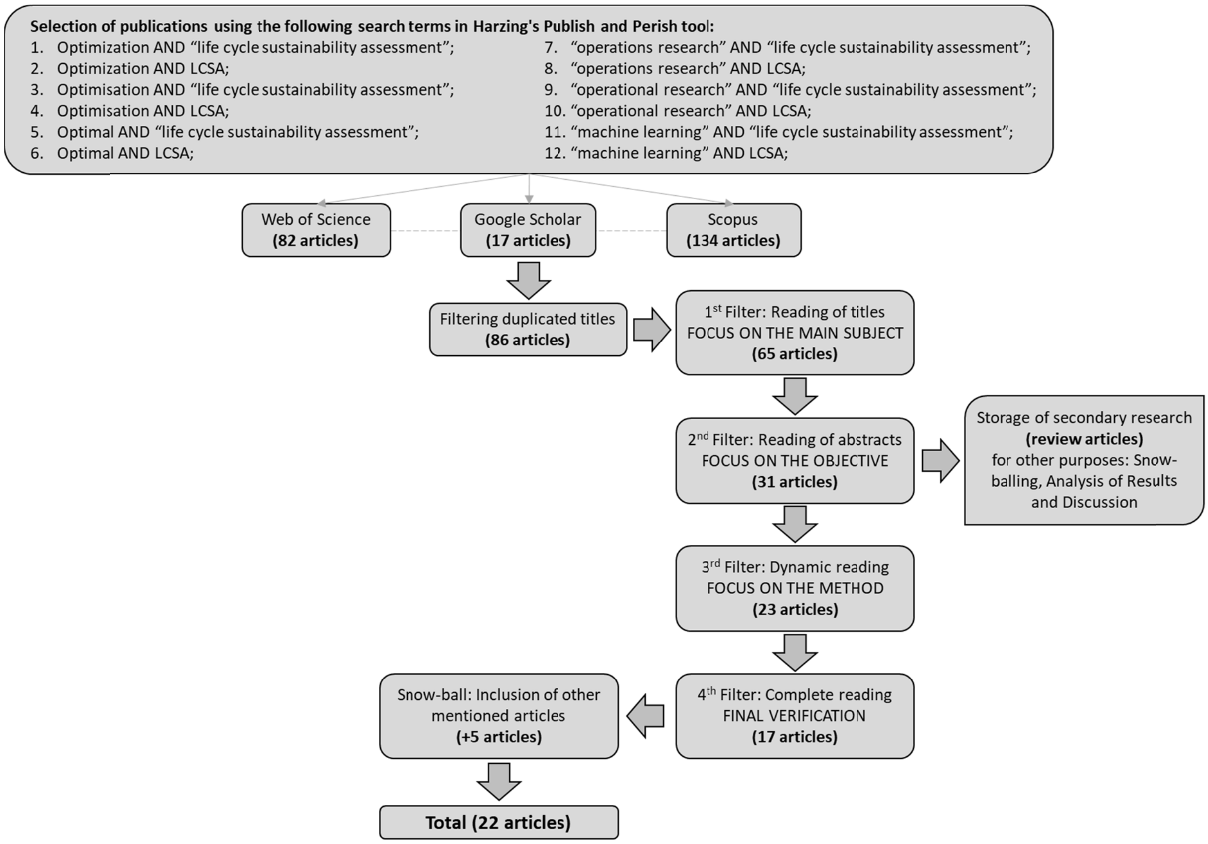

Figure 1. Structure of the systematic literature review and numbers of articles selected

For 86 selected publications, the article selection process consists of 5 stages: first filtering, second filtering, third filtering, fourth filtering, and finally snowballing.

Regarding the approach, exclusion and selection criteria in each phase, the first filter focused on screening only by reading the titles. Thus, articles unrelated to the topic were excluded. For example, those that did not make an LCSA or only referred to an assessment, such as S-LCA or LCC. At this point, the researchers deleted duplicate titles that the automatic exclusion had not detected. After this filtering, the next step left 65 publications.

The second filter provides for reading the abstracts of the publications, focusing on finding the objective of the study. All materials that were not published in the form of articles, such as books, dissertations, and theses, were excluded. In addition, scholarly secondary sources, such as literature reviews, were excluded at this stage. However, the reviews found were included in a separate file to complement the theoretical framework and contribute to the methodology for analyzing the results and discussing the proposed SLR. In addition, these reviews are used to search for articles that were not selected with the search terms to be added in the final stage of the snowballing process. Beyond the duplicate references found, this process also deleted citations that were not available in electronic media. This step also screened out studies that addressed performance evaluation or efficiency assessment methods (DEA) that focused on something other than the application of optimization to decision making-even if they used little-researched techniques in this area, such as machine learning. The same is true for research that only explored and proposed conceptual frameworks (theoretical frameworks) without applications. In addition, articles were excluded that were out of context or applied optimization to only one or more dimensions of sustainability, e.g., only optimizing E-LCA and LCC, even if they proposed theoretically how to apply it. Thus, after this screening, 31 articles remained to be selected.

The third filter, dynamic reading, assumes that only primary scientific research methods are selected. Thus, applications that were simply LCSA applications for project comparisons or scenario analyzes without the use of optimization techniques were excluded. In this step, the remaining research papers that presented only conceptual frameworks (theoretical frameworks) or new constructs without applications were screened out. In one particular case, an article was excluded because it claimed to deal with LCSA. However, what were labeled as social indicators were E-LCA indicators categorized as damage to human health. Of this selection, 23 articles remained.

The second to last step requires a full reading of the articles and review of the results. This fourth filtering excluded studies that proposed a model with approaches to the three dimensions of LCSA but did not use S-LCA indicators in validation through a case study. At the beginning of the selection process, some articles were not available. Therefore, these publications were requested from the institution's library and their authors. However, two book chapters could not be obtained through available scientific-technical partnerships (Note 3) and were excluded in this final selection step. After this final filtering, 17 articles remained.

In the snowballing step, used in SLRs, the reference lists of selected articles are analyzed to collect further studies (Dresch, Lacerda, & Antunes, 2015). In this work, literature reports found on the topic were selected and saved after the second filtering. So, at this point, literature that met the search requirements but for some reason was not selected by the predefined search method was added to the final list of articles. Articles from the review by Thies et al. (2019) were mainly included in this review. Subsequently, it was determined that the review did not include any articles through 2017 that used MODM techniques and LCSA to approximate the three dimensions of sustainability. In addition, articles that proposed methods using weighted sum methods (MADM), AHP, and fuzzy sets were not included as exclusion criteria. The reason for this exclusion is that the use of these techniques is already quite common in the literature along with proposals for weighting and normalization (Thies et al., 2019), but they have several shortcomings, such as the fact that they do not necessarily guarantee that the final solution is acceptable (Marler & Arora, 2004, 2010). Articles that use nonparametric techniques of efficiency analysis, such as Data Envelopment Analysis (DEA), which does not explicitly aim at optimization, were not selected. Thus, the selection criterion includes only articles that have dealt in some way with optimization techniques using deterministic, stochastic, or artificial intelligence models. One exception (Kucukvar et al., 2014a) used MADM methods, but the article complemented the other study selected by the fourth filter (Kucukvar et al., 2014b). Five more articles were included in the final selection by snowballing, resulting in a total of five articles (Ahmed & Sarkar, 2019; Chantrelle et al., 2011; Hammad et al., 2021; Kucukvar et al., 2014a; Mostavi, Asadi, & Boussaa, 2017) for a total of 22 articles to be analyzed.

3. Analysis of Selected Articles

The analysis model for the selected articles follows the structure published in the appendix of the review by Thies et al. (2019). Introductory to the results, Table 3 and Figure 2 show that the first article in the literature dealing with LCSA and OR with application to buildings was published in 2011 (Chantrelle et al., 2011). However, since LCSA historically did not gain prominence until this year with the publication of UNEP/SETAC (2011), the authors had not yet used the term LCSA at the time of publication. For this reason, this publication was only found through the snowballing stage in article selection. For the same reason, a two-year gap (2012-2013) with no publications on the topic was also found. Although additional research on the topic published through 2013 appears in the study by Thies et al. (2019), it focuses only on MADM methods and does not use MODM, DEA, or other heuristic methods and was therefore discarded during the snowballing phase of this literature review.

Thus, it is only in 2014 that we can see a new movement focusing on road construction, followed by 2015 for the energy sector, 2016 began studies on electricity and vehicles, 2017 on concrete structures, 2018 on industrial systems, 2019 on supply chains and companies (organisational), 2020 on nexus (interconnections) and chemicals, and 2021 on the use of water in coal mining. Given the relatively small number of articles addressing and applying LCSA and OR, a potential novelty to this topic is seen as the literature has only effectively integrated the two objects since 2014. In addition, there is a slow but steady upward trend (growth) in the number of articles published on this topic—despite a decrease of one article in 2015 and 2017 and two articles in 2021—as the time horizon to March 2022 includes two articles published only in the latter year.

Table 3. List of selected articles by product and year of publication

Quote	Product	2011	2012	2013	2014	2015	2016	2017	2018	2019	2020	2021	2022
(AHMED; SARKAR, 2019)	Supply									x			
(GUO et al., 2020)	Chain										x		
(CHANTRELLE et al., 2011)	Buildings	x											
(MOSTAVI; ASADI; BOUSSAA, 2017)								x					
(TOOSI; LAVAGNA, 2019)										x			
(HAMMAD et al., 2021)												x	
(LIN et al., 2022)													x
(TOOSI et al., 2022)													x
(AZAPAGIC et al., 2016)	Electricity						x						
(TARNE; LEHMANN; FINKBEINER, 2019)	Companies									x			
(WANG et al., 2017)	Structure							x					
(REN et al., 2015)	Energy					x							
(KUCUKVAR et al., 2014a)	Pavements				x								
(KUCUKVAR et al., 2014b)					x								
(ZHENG et al., 2019)										x			
(ZHANG et al., 2020)	Chemical Products										x		
(REN, 2018)	Industrial								x				
(REN et al., 2018)	Systems								x				
(REN et al., 2020)											x		
(YANG; GUO, 2021)	Water usage											x	
(ONAT et al., 2016)	Vehicles						x						
(ONAT et al., 2020)											x		

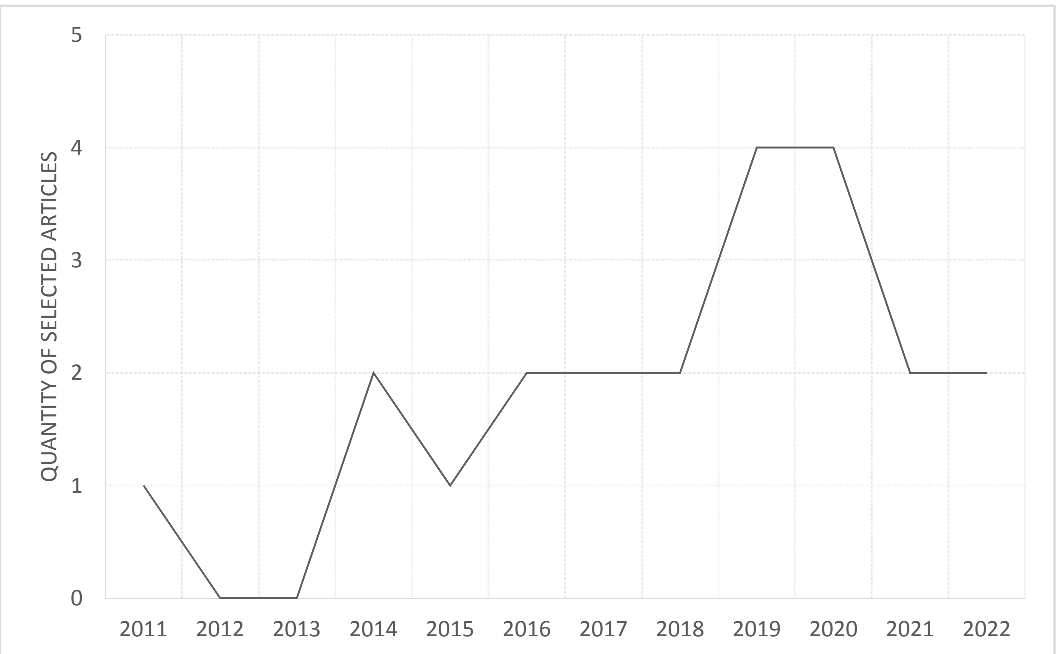

Figure 2. Trend Line chart of articles related to the subject

The analysis of the results of the scientific journals of the selected articles (Table 4) shows a diversity of journals and that methods integrating optimization and LCSA are often published for each product/system or application. Each case has elements that need to be analyzed and studied by experts in the field. This shows that OR and LCSA methods tend to be less general. In theory, the articles solve the research problems for each case and target.

Table 4. Relationship between the scientific journals and the quantity of selected articles

Scientific Journals	Number of Articles
The International Journal of Life Cycle Assessment	3
AIChE Journal	2
Computers & Chemical Engineering	2
Energy	2
Journal of Cleaner Production	2
Applied Energy	1
Automation in Construction	1
Building and Environment	1
Chemical Engineering Science	1
Energy Conversion and Management	1
Energy Reports	1
Geofluids	1
Journal of Asian Architecture and Building Engineering	1
Publication in Annals of Congress	1
Renewable and Sustainable Energy Reviews	1
Resources, Conservation and Recycling	1

However, within these applications in specific systems, projects, and products, it is possible to identify features in each proposed optimization model when integrated with LCSA. As shown in Table 5, different application scenarios can be identified in areas that involve the same industry.

For example, Ahmed and Sarkar (2019) explore options and tradeoffs for energy improvement, and Guo et al. (2020) assess the nexus between resources, food, and bioenergy in Southern Hemisphere countries.

Regarding buildings, six articles developed an optimization method based on LCSA. Three publications (Mostavi, Asadi, & Boussaa, 2017; Toosi & Lavagna, 2019; Hammad et al., 2021) were characterized by the use of techniques that select the best design from a set of alternatives, such as the choice between materials and architectural elements such as doors, walls, windows, roofs and others. In addition, all but one of the building studies suggest designing an optimal energy storage system (Toosi et al., 2022) to optimize architectural design mainly in terms of the building envelope. Only two articles (Toosi & Lavagna, 2019; Hammad et al., 2021) indicate that they have considered Building Information Modeling (BIM) at some point of the process, although no article addresses this subject. In addition, some of the studies that deal with buildings differ in that they use specific indicators for S-LCA, such as thermal comfort and job satisfaction, which are already accepted and used in this capacity in the literature on the subject (Janjua, Sarker, & Biswas, 2019, 2020; Toosi et al., 2020).

In the paving subject, there is consistency in all selected publications (Kucukvar et al., 2014a; Kucukvar et al., 2014b; Zheng et al., 2019) regarding the alternative product comparison scenario for product evaluation, although the Zheng et al. (2019) method for selecting pavement maintenance products differs from the others in this analysis.

In terms of product system boundaries, the publications by Ren (2018) and Ren et al. (2020) present methods aimed at identifying the leading driving indicators (drivers) of product or system sustainability, while the publication by Ren et al. (2018) focuses on the development of the product by selecting the best design from a set of alternatives.

Regarding vehicle studies, although one study focuses on electric cars and another on passenger cars, the same application scenario applies to both: product evaluation by comparing alternative solutions or production processes (Onat et al., 2016; Onat et al., 2020).

The other applications-electricity, enterprise, structural, energy, chemical, and water use-are not discussed in relation to the product system boundary because only a selected point is included in this review, as shown in the results in Table 5. In general, there is a higher frequency of articles that suggest evaluation by comparing alternative products/supply chains/production processes, followed by those that use optimization for product development in selecting the best design from a range of alternatives.

Table 5. Product system boundary of the optimization techniques and LCSA

Quote	**Product / application**	**Product / application specific characteristics**	**Product System Border**					
			Product Development		**Product improvement**		**Product evaluation**	
			Selecting the best design from a set of alternatives	**Design of the ideal product / design (system)**	**Exploration of improvement options and trade-offs**	**Evaluation / selection of alternatives improving**	**Identify the main sustainability *drivers* (product or system)**	**Comparison of alternative products / supply chains / production processes**
(AHMED; SARKAR, 2019)	Supply Chain	Energy Supply Chain			x			
(GUO et al., 2020)		Resource-food-bioenergy nexus, Southern Hemisphere						x
(CHANTRELLE et al., 2011)	Buildings	Community building renovation (school) - architectural project envelope				x		
(MOSTAVI; ASADI; BOUSSAA, 2017)		Architectural design of commercial buildings	x					
(TOOSI; LAVAGNA, 2019)		Building envelope (mentions BIM)	x					
(HAMMAD et al., 2021)		Buildings (residential and commercial - cites BIM)	x					
(LIN et al., 2022)		Residential buildings (operation and maintenance)						x
(TOOSI et al., 2022)		Building (system for storing energy)		x				
(AZAPAGIC et al., 2016)	Electricity	Electricity		x				x
(TARNE; LEHMANN; FINKBEINER, 2019)	Companies	Companies (organizational)			x			
(WANG et al., 2017)	Structures	Bridges	x					
(REN et al., 2015)	Energy	Bioethanol	x					
(KUCUKVAR et al., 2014a)	Pavement	Pavement						x
(KUCUKVAR et al., 2014b)		Pavement						x
(ZHENG et al., 2019)		Pavement Maintenance						x
(ZHANG et al., 2020)	Chemical Products	Chemical Products	x					
(REN, 2018)	Industrial Systems	Industrial Systems					x	
(REN et al., 2018)		Industrial Systems	x					
(REN et al., 2020)		Industrial Systems					x	
(YANG; GUO, 2021)	Water usage	Water use in coal mining					x	
(ONAT et al., 2016)	Vehicles	Passenger Cars						x
(ONAT et al., 2020)		Electric Vehicles						x

Marler and Arora (2004) provided an overview of nonlinear multi-objective optimization (MOO) methods, which help classify different approaches based on how preferences are handled in the optimization process and are divided into three main categories:

1) Methods with a priori preference articulation: these methods require the user to specify the relative

importance or preferences of the objective functions or desired goals before running the optimization algorithm. The user's preferences guide the optimization process, and the algorithm attempts to find solutions that satisfy these preferences.

2) Methods with a posteriori preference articulation: in these methods, a set of mathematically equivalent solutions, also called a Pareto front or Pareto set, is generated during the optimization process. The user then selects a single solution from this set based on his preferences or decision criteria.

3) Methods without specifying preferences: This category includes methods that do not explicitly consider preference articulation during the optimization process. These methods often focus on exploring the entire Pareto front or generating a variety of solutions without requiring specific preference information.

This classification was used to analyze the methods of the selected studies and is presented in Table 6—"Articulation" column. Of all the articles analyzed, twelve studies (54.5%) use a priori preference articulation methods, and eleven use MCDA techniques, except one that applies the lexicographic optimization method with the ε-restriction approach. Six studies (27.3%) presented methods classified with a posteriori preference articulation, in which the decision maker selects the preferred solution after generating the set of Pareto-optimal solutions. Of these six studies, five applied to cases of buildings and the other chemicals. All of them used MODM-type techniques. For the building applications, two used heuristic techniques, another two used artificial intelligence, and one used the Mixed Integer Nonlinear Programming Method (MINLP). In the case of the chemical study, the other application used branch-and-bound rule-based algorithms and the ε-restricted method for Pareto analysis. The latter case meets the discussion of Thies et al. (2019), which justifies the employability of advanced MODM solution procedures by using the multi-objective branch-and-bound¸ algorithm since it makes it possible to handle more objectives simultaneously while keeping the computational effort at a reasonable level. Meanwhile, meta-heuristic algorithms such as NSGA do not guarantee the optimality of the solution and should be avoided (Gendreau & Potvin, 2010 apud Thies et al., 2019). Finally, four papers (18.2%) used methods without preference articulation: three based on a Compromise Programming Model and one on a centralized and decentralized Integer Programming Model (based on game theory and Nash equilibrium) coupled with an agent-based Model.

Table 6 also shows how the OR works in different segments. One can use different techniques to reach a particular solution and guide decision making. When asked which method is the best, Marler and Arora (2004) have already answered that no approach is better than the other. The selection of a particular method depends on the type of information contained in the problem, user preferences, solution requirements, and software availability. However, the authors emphasize that methods that provide necessary and sufficient conditions for Pareto optimization are preferable.

Nevertheless, we want to define a particular method that is the best among those presented. In this case, we can design a study following the example of Nabipour-Afrouzi et al. (2018). In this case, the authors not only studied a single topic—photovoltaic-wind hybrid system—according to the literature review, but also analyzed the optimization techniques found using an analytical model created after applying the different methods in the same case study. In this way, it is possible not only to revalidate the methods, but also to compare and define which optimization technique is the most suitable for this application, taking into account, for example, accuracy, time required, complexity and other previously defined criteria.

Table 6. Optimization techniques, their characteristics and tools used in the selected studies

Quote	**Product / application**	**Characteristics of optimization techniques**					**Methods, models, techniques and algorithms used**	**Articulation**	**Tools used**
		Deterministic	**Stochastic**	**MADM**	**IA**	**Meta-heuristics**			
(AHMED; SARKAR, 2019)	Supply Chain	x					Lexicographic optimization method with ε-restriction approach	*A priori*	Not mentioned
(GUO et al., 2020)		x	x				Centralized optimization (MIP) and decentralized optimization (MIP based on game theory - Nash equilibrium) + Agent-based modeling	No articulation	Not mentioned
(CHANTRELLE et al., 2011)	Buildings		x			x	Genetic algorithm (NSGA-II) coupled with TRNSYS (simulator)	*Hindsight*	MultiOpt
(MOSTAVI; ASADI; BOUSSAA, 2017)			x			x	Harmony Search Algorithm (HS)	*Hindsight*	C# code in EnergyPlus
(TOOSI; LAVAGNA, 2019)					x		Evolutionary Algorithms	*Hindsight*	Rhino-Grasshopper (Honeybee+Galapagos) +EnergyPlus
(HAMMAD et al., 2021)		x					Mixed Integer Nonlinear Programming Method (MINLP)	*Hindsight*	Python (+ Revit + EnergyPlus)
(LIN et al., 2022)				x			AHP + Utility Theory + fuzzy logic	*A priori*	Not mentioned
(TOOSI et al., 2022)					x		Machine Learning	*Hindsight*	Grasshopper + Energy plus + Matlab
(AZAPAGIC et al., 2016)	Electricity	x		x			Mixed Integer Linear Programming (MILP) + Analytic Hierarchy Process (AHP) + Multi-attribute Value Theory (MAVT)	*A priori*	SSAT + Web-HIPRE
(TARNE; LEHMANN; FINKBEINER, 2019)	Companies			x			Multi-Criteria Decision Analysis Method (MCDA) and Conjoint Analysis	*A priori*	Not mentioned
(WANG et al., 2017)	Structures			x			AHP + Weighted Global Criteria Method	*A priori*	Not mentioned
(REN et al., 2015)	Energy			x			Combined AHP-VIKOR Method	*A priori*	Not mentioned
(KUCUKVAR et al., 2014a)	Pavement			x			Intuitionistic Fuzzy Sets + Technique for Order of Preference by Similarity to Ideal Solution (TOPSIS)	*A priori*	Not mentioned
(KUCUKVAR et al., 2014b)			x	x			Commitment Programming Template	No articulation	Matlab
(ZHENG et al., 2019)				x			Combined AHP+VIKOR Method	*A priori*	Not mentioned
(ZHANG et al., 2020)	Chemical Products	x					Rule-based *branch-and-bound* algorithms and ε-restriction method for Pareto analysis	*Hindsight*	BARON global solver in GAMS 24.7.4
(REN, 2018)	Industrial Systems	x		x			Goal scheduling model based on interval preference relation: Multiplicative and Fuzzy	*A priori*	Not mentioned
(REN et al., 2018)				x			Multi-actor multi-criteria decision-making method: Best-best range method + Interactive Multi-criteria Decision Making	*A priori*	Not mentioned

(REN et al., 2020)		x		x	Hybrid multi-criteria decision-making method: fuzzy multi-actor method best-worst interval + Linear Programming Model	*A priori*	Not mentioned
(YANG; GUO, 2021)	Water usage		x	x	AHP + CRITIC + Game Theory Method and CW-VIKOR	*A priori*	Not mentioned
(ONAT et al., 2016)	Vehicles			x	Commitment Programming Template	No articulation	Matlab
(ONAT et al., 2020)				x	Commitment Programming Template	No articulation	LINGO

Table 7, Table 8 and Table 9 show the results of the life cycle sustainability assessment indicators used for the applications of each selected study. For the environmental indicators, there is an almost universal concern about the global warming potential (79.17% of the studies include this indicator). In the economic indicators, costs are very common (83.33%). Among the social indicators, direct job creation is the most represented (37.5%); however, this dimension requires a greater consensus on the importance of using LCSA indicators than the others. In addition, it can be noted that the selection of indicators changes depending on the context of use. For example, in the case of buildings, the authors consider thermal comfort or customer satisfaction as the primary and only social indicator in the design of a building. Therefore, one wonders: is it enough to consider only this indicator to create an S-LCA of buildings?

Table 7. Environmental indicators used for the LCSA of the selected study applications

Quote	Product / application	Environmental Dimension																					
		global warming	depletion of the ozone layer	photochemical oxidant formation	particulate matter	acidification	eutrophication	ionizing radiation	abiotic resource/depletion	toxicity	energy	water	materials	land use	recyclability	waste	smog	human health	ecosystem	resources	environmental costs	environmental impact score (index)	other environmental
(IZADIKHAH; SAEN, 2018)	Supply Chain												x			x					x		
(AHMED; SARKAR, 2019)		x																					
(GUO et al., 2020)		x	x	x		x	x		x	x													x
(CHANTRELLE et al., 2011)	Buildings	x									x												
(MOSTAVI; ASADI; BOUSSAA, 2017)											x												
(TOOSI; LAVAGNA, 2019)		x	x	x		x	x		x	x	x												
(HAMMAD et al., 2021)																							x
(LIN et al., 2022)																							x
(TOOSI et al., 2022)		x	x	x		x	x													x		x	
(AZAPAGIC et al., 2016)	Electricity	x	x	x		x				x				x	x								
(GALÁN-MARTÍN et al., 2016)		x	x	x		x	x			x				x						x			
(TARNE; LEHMANN; FINKBEINER, 2019)	Companies	x																					
(WANG et al., 2017)	Structures										x							x	x	x		x	
(REN et al., 2015)	Energy	x			x	x				x													
(KUCUKVAR et al., 2014a)	Pavement	x								x	x	x		x		x							x
(KUCUKVAR et al., 2014b)		x								x	x	x		x		x							x
(ZHENG et al., 2019)		x				x	x										x	x					
(ZHANG et al., 2020)	Chemical Products	x	x	x	x	x	x	x		x		x		x						x			x
(REN, 2018)	Industrial Systems	x				x								x			x						
(REN et al., 2018)		x	x	x		x				x													
(REN et al., 2020)		x				x																	
(YANG; GUO, 2021)	Water usage	x				x	x			x		x								x			x
(ONAT et al., 2016)	Vehicles	x									x	x		x		x							x
(ONAT et al., 2020)		x		x	x						x	x		x				x					

Source: Based on the study by Thies et al., 2019.

Table 8. Economic indicators used for the LCSA of the selected study applications

Quote	Application / Product	Economic Dimension												
		costs	tax	import	Gross Domestic Product (GDP)	Gross Operating Surplus (GOS)	income	price	economic production	net present value	economic risk	technoeconomic characteristics	economic impact score (index)	other savings
(IZADIKHAH; SAEN, 2018)	Supply Chain	x					x	x						
(AHMED; SARKAR, 2019)		x												
(GUO et al., 2020)		x	x				x							x
(CHANTRELLE et al., 2011)	Buildings	x												
(MOSTAVI; ASADI; BOUSSAA, 2017)		x												
(TOOSI; LAVAGNA, 2019)		x												x
(HAMMAD et al., 2021)		x												
(LIN et al., 2022)												x		x
(TOOSI et al., 2022)		x											x	x
(AZAPAGIC et al., 2016)	Electricity	x										x		x
(GALÁN-MARTÍN et al., 2016)		x												
(TARNE; LEHMANN; FINKBEINER, 2019)	Companies	x												
(WANG et al., 2017)	Structures	x											x	
(REN et al., 2015)	Energy	x							x					
(KUCUKVAR et al., 2014a)	Pavement		x	x		x	x							
(KUCUKVAR et al., 2014b)			x	x		x	x							
(ZHENG et al., 2019)		x												
(ZHANG et al., 2020)	Chemical Products	x												
(REN, 2018)	Industrial Systems	x												
(REN et al., 2018)		x								x				
(REN et al., 2020)		x										x		
(YANG; GUO, 2021)	Water usage	x										x		x
(ONAT et al., 2016)	Vehicles			x	x	x								
(ONAT et al., 2020)		x			x	x								

Source: Based on the study by Thies et al., 2019.

Table 9. Social indicators used for the LCSA of the selected study applications

Quote	**Application / Product**	**Social Dimension**																									
		fair opportunities	**social benefits**	**education and culture**	**child labor**	**fair wage**	**professional growth**	**stakeholders in the supply chain**	**discrimination**	**safe/healthy living conditions**	**community engagement**	**work day**	**worker injuries**	**income**	**tax**	**direct employment**	**contribution to Economic Development**	**contribution to Technological Development**	**impacts on human health**	**compliance with environmental regulations**	**safe food**	**thermal/light comfort**	**customer satisfaction**	**health and safety**	**social risks**	**social impact score (index)**	**other social**
(IZADIKHAH; SAEN, 2018)	Supply Chain																							x			x
(AHMED; SARKAR, 2019)																x											
(GUO et al., 2020)								x																			
(CHANTRELLE et al., 2011)	Buildings																					x					
(MOSTAVI; ASADI; BOUSSAA, 2017)																							x				
(TOOSI; LAVAGNA, 2019)																							x				
(HAMMAD et al., 2021)																						x					
(LIN et al., 2022)										x													x	x			x
(TOOSI et al., 2022)																										x	x
(AZAPAGIC et al., 2016)	Electricity	x											x			x			x								x
(GALÁN-MARTÍN et al., 2016)													x			x											x
(TARNE; LEHMANN; FINKBEINER, 2019)	Companies																								x		
(WANG et al., 2017)	Structures		x	x						x																x	
(REN et al., 2015)	Energy		x														x				x						
(KUCUKVAR et al., 2014a)	Pavement												x			x											
(KUCUKVAR et al., 2014b)													x			x											
(ZHENG et al., 2019)							x			x		x						x						x			x
(ZHANG et al., 2020)	Chemical Products															x											
(REN, 2018)	Industrial															x			x								
(REN et al., 2018)	Systems		x		x	x			x		x						x							x			
(REN et al., 2020)											x																
(YANG; GUO, 2021)	Water usage																			x							x
(ONAT et al., 2016)	Vehicles												x	x	x	x											
(ONAT et al., 2020)															x	x											x

Source: Based on the study by Thies et al., 2019.

4. Conclusion and Suggestions for Future Research

This research followed the analysis model published in the appendix of the review by Thies et al. (2019) to analyze the selected articles. Based on the analysis of the selected articles, several key findings and recommendations for future research emerge.

The integration of Life Cycle Sustainability Assessment (LCSA) and Operations Research (OR) gained prominence starting in 2014, with the first publication on this topic appearing in 2011. It is worth noting that there was a two-year gap from 2012 to 2013 when no publications on LCSA and OR were identified. However, overall, the number of articles addressing this integration has shown a gradual upward trend, with occasional drops in certain years.

The review revealed that there are a variety of journals and that methods integrating optimization and LCSA are often published explicitly for each product/system or application. Each case has elements that need to be analyzed and studied by experts in the field. The OR and LCSA methods are less general and are developed according to the objectives.

Nevertheless, within these applications in specific products, projects and products, it is possible to identify features in each optimization model proposal when integrated with LCSA. In general, we see a higher frequency of articles that propose to evaluate alternative products/supply chains/production processes by comparison, followed by those that use optimization for product development in selecting the best design from a set of alternatives.

This research confirms that OR operates in multiple domains and that different techniques can provide a specific solution and decision support. Therefore, the optimization techniques found here or in other literature reviews should be evaluated against an established analytical model by applying them to the same case study. It is not only possible to revalidate the methods, but also to compare and define which integrated optimization technique is more satisfactory for the particular application, taking into account—for example, criteria such as accuracy, time required and complexity can be defined beforehand.

Furthermore, the selected studies considered various sustainability indicators, with global warming potential and costs being commonly addressed, although the choice of indicators may vary depending on the specific context of the application.

In conclusion, this research highlights the importance of analyzing and studying each product, project, or system individually within the context of OR and LCSA integration. The optimization models proposed are often specific to particular objectives and applications. Future research should focus on further validating and comparing these integrated optimization techniques using consistent analytical models and predefined evaluation criteria.

Acknowledgements

This work was supported by a Scholarship from Federal University of Technology – Paraná (UTFPR)

References

Ahmed, W., & Sarkar, B. (2019). Management of next-generation energy using a triple bottom line approach under a supply chain framework. Resources, Conservation and Recycling, v. 150, p. 104431, 1 Nov. 2019. https://doi.org/10.1016/j.resconrec.2019.104431

Arora, J. (2004). *Introduction to optimum design* (2nd ed.). California, USA: Elsevier Academic Press. https://doi.org/10.1016/B978-012064155-0/50012-4

Azapagic, A. et al. (2016). Towards sustainable production and consumption: A novel DEcision-Support Framework IntegRating Economic, Environmental and Social Sustainability (DESIRES) (vol. 91, pp. 93–103). Computers & Chemical Engineering, 12th International Symposium on Process Systems Engineering & 25th European Symposium of Computer Aided Process Engineering (PSE-2015/ESCAPE-25), 31 May–4 June 2015, Copenhagen, Denmark.

Belfiore, P., & Favero, L. P. (2013). *Pesquisa Operacional para cursos de Engenharia*. Elsevier Brasil.

Chantrelle, F. P. et al. (20110. Development of a multi-criteria tool for optimizing the renovation of buildings. *Applied Energy*, *88*(4), 1386–1394. https://doi.org/10.1016/j.apenergy.2010.10.002

Costa, D., Quinteiro, P., & Dias, A. C. (2019). A systematic review of life cycle sustainability assessment: Current state, methodological challenges, and implementation issues. *Science of The Total Environment*, *686*, 774–787. https://doi.org/10.1016/j.scitotenv.2019.05.435

Dresch, A., Lacerda, D. P., & Antunes, J. A. V. (2015). *Design Science Research: Research Method for Advancing Science and Technology* (Bookman Editora). https://doi.org/10.1007/978-3-319-07374-3

Eilon, S. et al. (2018). *Operations research*. 12 Sep. 2018. (Technical note).

Eom, S., & Kim, E. (2006). A Survey of Decision Support System Applications (1995–2001). *Journal of the Operational Research Society*, *57*, 1264–1278. https://doi.org/10.1057/palgrave.jors.2602140

Gendreau, M., & Potvin, J.-Y. (2010). *Handbook of Metaheuristics* (vol. 2). New York, NY: Springer. https://doi.org/10.1007/978-1-4419-1665-5

Golbarg, M. C., & Luna, H. P. L. (2000). *Otimização combinatória e programação linear*. Rio de Janeiro: CAMPUS.

Guo, M. et al. (2020). Multi-level system modelling of the resource-food-bioenergy nexus in the global south. *Energy*, *197*, 117196. https://doi.org/10.1016/j.energy.2020.117196

Hammad, A. W. A. et al. (2021). Enhancing the passive design of buildings: A mixed integer nonlinear programming approach for the selection of building materials and construction building systems. *Energy Reports*, *7*, 8162–8175. https://doi.org/10.1016/j.egyr.2021.04.063

Harzing, A. W. (2020). *Publish or Perish*. Retrieved June 1, 2022, from https://harzing.com/resources/publish-or-perish

Ho, W., Xu, X., & Dey, P. K. (2010). Multi-criteria decision making approaches for supplier evaluation and selection: A literature review. *European Journal of Operational Research*, *202*(1), 16–24. https://doi.org/10.1016/j.ejor.2009.05.009

Janjua, S. Y., Sarker, P. K., & Biswas, W. K. (2019). Sustainability assessment of a residential building using a life cycle assessment approach. *Chemical Engineering Transactions*, *72*, 19–24.

Janjua, S. Y., Sarker, P. K., & Biswas, W. K. (2020). Development of triple bottom line indicators for life cycle sustainability assessment of residential bulidings. *Journal of Environmental Management*, *264*, 110476. https://doi.org/10.1016/j.jenvman.2020.110476

Kolepffer, W. (2008). Life cycle sustainability assessment of products: (with Comments by Helias A. Udo de Haes). *The International Journal of Life Cycle Assessment*, *13*(2), 89–95. https://doi.org/10.1065/lca2008.02.376

Kucukvar, M. et al. (2014a). Ranking the sustainability performance of pavements: An intuitionistic fuzzy decision making method. *Automation in Construction*, *40*, 33–43. https://doi.org/10.1016/j.autcon.2013.12.009

Kucukvar, M. et al. (2014b). Stochastic decision modeling for sustainable pavement designs. *The International Journal of Life Cycle Assessment*, *19*(6), 1185–1199. https://doi.org/10.1007/s11367-014-0723-4

Lin, C.-C. et al. (2022). Cib-Utility Based Systems Framework for Existing Residential Building. *Journal of Asian Architecture and Building Engineering*, *21*(3), 755–765. https://doi.org/10.1080/13467581.2021.1902333

Marler, R. T., & Arora, J. S. (2004). Survey of multi-objective optimization methods for engineering. *Structural and Multidisciplinary Optimization*, *26*(6), 369–395. https://doi.org/10.1007/s00158-003-0368-6

Marler, R. T., & Arora, J. S. (2010). The weighted sum method for multi-objective optimization: new insights. *Structural and Multidisciplinary Optimization*, *41*(6), 853–862. https://doi.org/10.1007/s00158-009-0460-7

Mostavi, E., Asadi, S., & Boussaa, D. (2017). Development of a new methodology to optimize building life cycle cost, environmental impacts, and occupant satisfaction. *Energy*, *121*, 606–615. https://doi.org/10.1016/j.energy.2017.01.049

Nabipour-Afrouzi, H. et al. (2018). *Comprehensive Review on Appropriate Sizing and Optimization Technique of Hybrid PV-Wind System*. 2018 IEEE PES Asia-Pacific Power and Energy Engineering Conference (APPEEC). Proceedings. https://doi.org/10.1109/APPEEC.2018.8566269

Onat, N. C. et al. (2016). Combined application of multi-criteria optimization and life-cycle sustainability assessment for optimal distribution of alternative passenger cars in U.S. *Journal of Cleaner Production*, *112*, 291–307. https://doi.org/10.1016/j.jclepro.2015.09.021

Onat, N. C. et al. (2020). From sustainability assessment to sustainability management for policy development: The case for electric vehicles. *Energy Conversion and Management*, *216*, 112937. https://doi.org/10.1016/j.enconman.2020.112937

Pohekar, S. D., & Ramachandran, M. (2004). Application of multi-criteria decision making to sustainable energy planning—A review. *Renewable and Sustainable Energy Reviews*, *8*(4), 365–381.

https://doi.org/10.1016/j.rser.2003.12.007

Ren, J. et al. (2015). Prioritization of bioethanol production pathways in China based on life cycle sustainability assessment and multicriteria decision-making. *The International Journal of Life Cycle Assessment*, *20*(6), 842–853. https://doi.org/10.1007/s11367-015-0877-8

Ren, J. (2018). Life cycle aggregated sustainability index for the prioritization of industrial systems under data uncertainties. *Computers & Chemical Engineering*, *113*, 253–263. https://doi.org/10.1016/j.compchemeng.2018.03.015

Ren, J. et al. (2018). Multi-actor multi-criteria decision making for life cycle sustainability assessment under uncertainties. *AIChE Journal*, *64*(6), 2103–2112. https://doi.org/10.1002/aic.16149

Ren, J. et al. (2020). Industrial system prioritization using the sustainability-interval-index conceptual framework with life-cycle considerations. *AIChE Journal*, *66*(6), e16961. https://doi.org/10.1002/aic.16961

Tarne, P., Lehmann, A., & Finkbeiner, M. (2019). Introducing weights to life cycle sustainability assessment-how do decision-makers weight sustainability dimensions? *The International Journal of Life Cycle Assessment*, v. *24*(3), 530–542. https://doi.org/10.1007/s11367-018-1468-2

Thies, C. et al. (2019). Operations research for sustainability assessment of products: A review. *European Journal of Operational Research*, *274*(1), 1–21. https://doi.org/10.1016/j.ejor.2018.04.039

Toosi, H. A. et al. (2020). Life Cycle Sustainability Assessment in Building Energy Retrofitting; A Review. *Sustainable Cities and Society*, *60*, 102248. https://doi.org/10.1016/j.scs.2020.102248

Toosi, H. A. et al. (2022). A novel LCSA-Machine learning based optimization model for sustainable building design-A case study of energy storage systems. *Building and Environment*, *209*, 108656. https://doi.org/10.1016/j.buildenv.2021.108656

Toosi, H. A., & Lavagna, M. (2019). *Optimization and LCSA-based design method for energy retrofitting of existing buildings*. Designing Sustainability for All, Proceedings of the 3rd LeNS World Distributed Conference, Milano, Mexico City, Beijing, Bangalore, Curitiba, Cape Town. Proceedings.

UNEP/SETAC. (2011). *Towards a life cycle sustainability assessment: making informed choices on products*. France: UNEP/SETAC Life Cycle Initiative programme.

Visentin, C. et al. (2020). Life cycle sustainability assessment: A systematic literature review through the application perspective, indicators, and methodologies. *Journal of Cleaner Production*, *270*, 122509. https://doi.org/10.1016/j.jclepro.2020.122509

Wang, J. et al. (2017). Life cycle sustainability assessment of fly ash concrete structures. *Renewable and Sustainable Energy Reviews*, *80*, 1162–1174. https://doi.org/10.1016/j.rser.2017.05.232

Yang, J., & Guo, L. (2021). Dynamic Evaluation of Water Utilization Efficiency in Large Coal Mining Area Based on Life Cycle Sustainability Assessment Theory. *Geofluids*, *2021*, e7793988. https://doi.org/10.1155/2021/7793988

Yang, X.-S., & Koziel, S. (Eds.). (2013). Computational Optimization and Applications in Engineering and Industry (2011a ed., p. 359). Berlin Heidelberg: Springer. https://doi.org/10.1007/978-3-642-20986-4

Zheng, X. et al. (2019). Life-cycle sustainability assessment of pavement maintenance alternatives: Methodology and case study. *Journal of Cleaner Production*, 213, 659–672. https://doi.org/10.1016/j.jclepro.2018.12.227

Zhang, X. et al. (2020). Sustainable product design: A life-cycle approach. *Chemical Engineering Science*, *217*, 115508. https://doi.org/10.1016/j.ces.2020.115508

Notes

Note 1. The discipline of Operations Research is mainly part of the curriculum of undergraduate courses such as Production Engineering and Industrial Engineering.

Note 2. Some authors also refer to these as weighted sum methods (ARORA, 2004; MARLER; ARORA, 2004, 2010)

Note 3. Through CAPES Periodical Portal or COMUT (Brazilian Bibliographic Commutation Program).