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TOPICAL REVIEW

Artificial Intelligence-Based Life Cycle Engineering in Industrial Production: A Systematic Literature Review

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ABSTRACT For the last few years, cases of applying artificial intelligence (AI) to engineering activities towards sustainability have been reported. Life Cycle Engineering (LCE) provides a potential to systematically reach higher and productivity levels, owing to its holistic perspective and consideration of economic and environmental targets. To address the current gap to more systematic deployment of AI with LCE (AI-LCE) we have performed a systematic literature review emphasizing the three aspects:(1) the most prevalent AI techniques, (2) the current AI-improved LCE subfields and (3) the subfields with highly enhanced by AI. A specific set of inclusion and exclusion criteria were used to identify and select academic papers from several fields, i.e. production, logistics, marketing and supply chain and after the selection process described in the paper we ended up with 42 scientific papers. The study and analysis show that there are many AI-LCE papers addressing Sustainable Development Goals mainly addressing: Industry, Innovation, and Infrastructure; Sustainable Cities and Communities; and Responsible Consumption and Production. Overall, the papers give a picture of diverse AI techniques used in LCE. Production design and Maintenance and Repair are the top explored LCE subfields whereas logistics and Procurement are the least explored subareas. Research in AI-LCE is concentrated in a few dominating countries and especially countries with a strong research funding and focus on Industry 4.0; Germany is standing out with numbers of publications. The in-depth analysis of selected and relevant scientific papers are helpful in getting a more correct picture of the area which enables a more systematic approach to AI-LCE in the future.

INDEX TERMS Artificial intelligence, life cycle engineering, machine learning, sustainable development goal.

I. INTRODUCTION

With the growing digitalization of society, there is an increased interest in the use of artificial intelligence (AI) methods, techniques and algorithms. Life cycle engineering (LCE) is a key factor in moving towards a sustainable society, a major challenge for society. LCE has to overcome many obstacles to reach the goal of a sustainable society. Using AI and machine learning (ML) in LCE enables LCE to reach its goal of a sustainable industry and society faster.

Taking the importance of LCE into account and the need to move towards a sustainable and circular society, and how the use of AI enables new possibilities in so many areas, it is essential to explore how AI is used in LCE, considering the broad scope of AI methods, techniques and algorithms. This is also relevant for identifying gaps in using AI-LCE and gaps in research and identifying areas of high potential. This helps to identify how and where AI can support LCE and what factors are important to enable LCE to be open to AI. Although AI/ML is usually explored by the experts of the community, the use of AI/ML in LCE is still limited, which is the main focus of this study. Again, we even see a

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future where AI is the driver of LCE, dynamically optimizing economic and ecological goals. We hope this systematic analysis and synthesis will bring insights and understanding and enable a move towards AI-LCE [1].

Life cycle costs (LCCs) (e.g. pollution, production or other possible areas) need to be calculated more accurately in the future from societal and industrial perspectives. Currently, many LCCs are not included in the price of a product and are often left for taxpayers or future generations to deal with. However, the move towards a total LCC for production is ongoing and required in a sustainable society, and the move towards this goal will continue. Increasing LCC accuracy is an important area for LCE and will help industry and society to focus their resources on where they make the most progress. It is competitively necessary to have a good estimate of the total LCC since the costs have to be paid somewhere, and more of the costs will be included in the price of the product. This is also an important part of how society should navigate towards a sustainable society and meet Sustainable Development Goals (SDG). To make society more sustainable, the European Union (EU) introduced an emission trading system (ETS) in 2005. The ETS is the cornerstone of the EU's climate change strategy. It directs and monitors carbon emissions for the industry at a lower level, where allowances must be purchased or traded, thus increasing LCC.

A. RELATED WORKS

Currently, the worldwide economic downturn leads manufacturer and their suppliers to cut costs and enhance their performances. Additionally, environmental protection is becoming more important, and green manufacturing got an expected practice. Based on those recognitions, in the early stage of product design, environmental impacts must be weighed, balanced and optimized against other concerns, such as LCC, availability and time to market. These multiple and often conflicting objectives pose a challenging and complex optimization problem. Thus, the focus is moved from the single methodology towards their integration and optimization. With this aim, a new term, namely, product life cycle optimization (PLCO), has been coined to identify such problems. A PLCO multi-objective model has been proposed, which optimizes simultaneously along the product life cycle, costs, environmental impacts and performance values [2].

Global warming effects have become very apparent in many parts of the world, causing governments to force their industries to be environmentally conscious. Small individual contributions will help abate global warming. A life cycle assessment (LCA) for steel balls used as grinding media in mines produced at Craster International in Zimbabwe is discussed in [3]. It is essential to know the life cycle environmental impacts of steel balls since they produce greenhouse gasses in their production. The emitted carbon dioxide, sulfur dioxide, nitrous oxide and other trace greenhouse gasses have adverse effects on flora, fauna, water bodies and humans. Interviews, questionnaires and direct observation and measurements were used to generate the data. The data were analyzed, and a new LCA diagram from the results of the research and recommendations was made. Engineering must change the current focus on eco-efficiency to a search for solutions that are effective in terms of operating within the share of the total pollution space that they can claim. Engineering for environmental sustainability must be life cycle engineering, and the paper positions it relative to the constraints given by the boundaries of the ecosystems, the targets of the United Nations' sustainable development goals and the strategies for a circular economy [4].

The paper [4] focused on the LCE of production, use and recovery of self-chilling beverage cans. An attributional LCA has been undertaken considering all life cycle stages of a self-chilling can: manufacture of each part of the beverage container, its utilization, collection of the user can and management of the waste by reuse, recycling and landfilling. Activated carbon production is included in detail to assess its contribution to the overall life cycle. The results are compared with those of conventional aluminium and steel beverage cans stored in two types of retail chiller: a single-door refrigerator and a large open-front cooler. A sensitivity analysis explores alternative scenarios for activated carbon production and recovery of the can components post-use for reuse or recycling. The results highlight the importance of using activated carbon produced from biomass through a process with efficient use of low-carbon electrical energy, energy recovery from waste streams and appropriate air pollution control and of achieving high rates of recovery, reuse and recycling of the cans after use. The results suggest limited markets into which the product might be introduced, particularly where it would displace inefficient chilled storage in an electricity system with a high proportion of coal-fired generation.

Manufacturing is becoming increasingly competitive, and economic margins shrink, requiring manufacturers and their suppliers to focus on cost reduction. To avoid unwanted environmental consequences from the use of several materials, it is necessary to consider all life cycle stages of a product system as early as possible in the product and process development activities. Life Cycle Engineering supports such a systemic perspective and thus contributes to the engineering of products with the lowest possible environmental impact. The core methodology of LCE is Life Cycle Assessment, which quantifies the environmental impacts of products and processes over their life cycle [55].

LCE builds up on the comprehension of domain-specific engineering activities and their interlinkage along the product life cycle. Its goal is to guide engineering processes through knowledge regarding hotspots and trade-offs in terms of environmental, social and economic impacts. However, LCE implementations show shortcomings due to a discontinuous integration in key business processes as well as separated tool environments between core engineering disciplines and LCE methods and tools [56]. There are also many modular products which consist of detachable modules, which can be manufactured, assembled, and serviced separately. Some of the modules may be reusable, recyclable or re-manufacturable upon product retirement. Thus, modular design can provide benefits to many aspects of the product life cycle. Different types of integrated modular design methodology can be useful for life cycle engineering such as [39].

Engineering for environmental sustainability must be LCE and the constraints given by the boundaries of the ecosystems, the targets of the United Nations' SDGs and the strategies for a circular economy [5]. This top–down perspective is combined with a bottom-up perspective from the product's life cycle and technology. For each stage of the life cycle, the contents of the toolbox for LCE are reviewed, and a perspective is given on how absolute environmental sustainability requirements can be incorporated into a target-driven LCE.

Increasing competitive pressure within industries producing long-living, cost-intensive products drives the need to optimize product life cycles in terms of faster time to market, sustainable operation, reengineering and recycling. In this context, the complexity of information technology (IT) systems is growing and has to connect different life cycle phases. There are still many challenges concerning interface problems between different IT systems. They are caused by different data formats, continuous demand for information or integration of new technologies. Thus, LCE has played a significant role and needs to consider integrating new Industry 4.0 solutions, such as cloud services, big data or cyber-physical systems. An overview of these challenges, future development and new research approaches have been presented [6].

LCE has evolved in parallel with other disciplines with similar aims. In addition to LCE, there exist many concepts, such as industrial ecology, cleaner production, life cycle management, industrial symbiosis and circular economy. Consequently, orientation becomes challenging, and a framework to integrate them is required. The paper [7] introduced an integrated framework for LCE defining the concept and its boundaries. It argues for the need to reorientate LCE towards the environmental dimension of sustainability.

II. METHODOLOGY

This section focuses on research questions and describes the process involved in conducting the systematic literature review (SLR) proposed in this paper following the guidelines developed by Kitchenham et al. [8].

A. THE RESEARCH QUESTION

Based on the literature review, three research questions have been prepared for this paper. The research questions are presented below.

RQ1: What are the main areas of manufacturing where LCE is dealt with/applied/conducted today or researched?

There are many manufacturing industries, such as energy production, home appliance industry and farming industry, where LCE technology is dealt with. The RQ1 investigates the main manufacturing areas where LCE is deployed.

RQ2: Which engineering activities of LCE adopted ML and AI?

RQ2.1: What ML/AI techniques/methods are used?

RQ2.2: What ML/AI tasks are used?

The second RQ2 highlights the ML/AL methods and their LCE tasks. There are two sub-RQs in RQ2 where RQ2.1 focuses on ML/AI techniques/methods, and RQ2.2 focuses on ML/AI tasks.

RQ3: What SDGs were they able to achieve?

The third RQ3 emphasises the global goals of SDG.

An SLR is a process for extracting, aggregating and synthesising data from primary studies to answer a set of specific research questions and generate a secondary study [9]. An SLR employs inclusion and exclusion criteria to filter the research works that will be included in the review. We incorporate a complementary guideline described in [10]. We also consider the recommendations on the importance of including a manual target search on popular venues, authors and journals as described in [11].

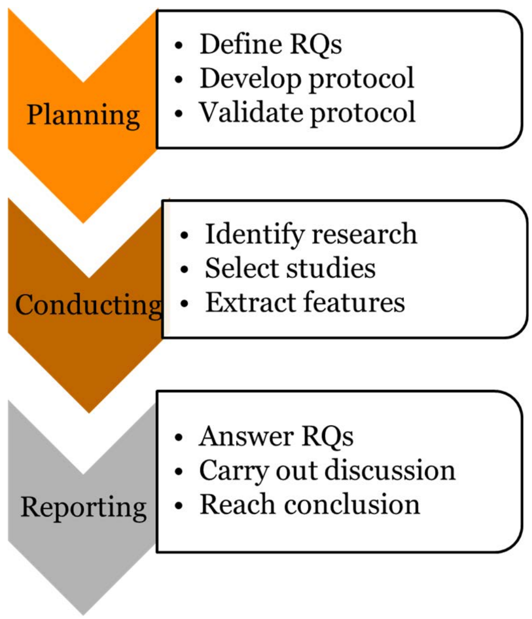

FIGURE 1. Systematic review process and tasks.

Generally, an SLR involves three phases, namely, (i) planning, (ii) conducting and (iii) documenting or reporting the review [12]. Planning involves the set-up activities, including defining the research question, search protocol and validation protocol. The review includes searching and filtering the studies, data extraction and schematisation. Documenting is the final phase and involves writing up the results, answering the research questions, making classifications and highlighting future work or potential trends. Figure 1 depicts these three phases.

B. PLANNING

An SLR approach was adopted in this paper. It paid attention to reviewing the current published works in LCE and obtaining an unprejudiced and objective summary of the current state of the art and future potential of AI and ML applications in LCE. SLR uses a proven scientific and replicable technique for accessing and understanding all existing relevant research on a topic question or phenomenon of interest [11]. Additionally, SLRs help researchers develop relevant insights based on the hypothetical synthesis of previous and current research and find potential gaps in the literature [13]. This study also presents and discusses a three-stage SLR technique approach: (i) preoperational ('review planning'), (ii) operational stage ('carrying out the review') and (ii) post-operational stage ('review findings').

C. CONDUCTING
Within the LCE domain, several areas use AI to offer adequate safety and an effective and efficient environment. Many research works have been conducted to enhance the LCE processes using AI. It aimed to study the application of AI and ML techniques in LCE. Specifically, we focus on the AI and ML methods discussed above (see Table 3). We sought to comprehend and appreciate how machine AI and ML methods will help make the LCE processes and systems safer and more efficient. To limit the scope of this paper, we conducted a keyword search in official publisher websites and academic databases, such as Springer, Elsevier, Scopus, Science Publication, Taylor & Francis,

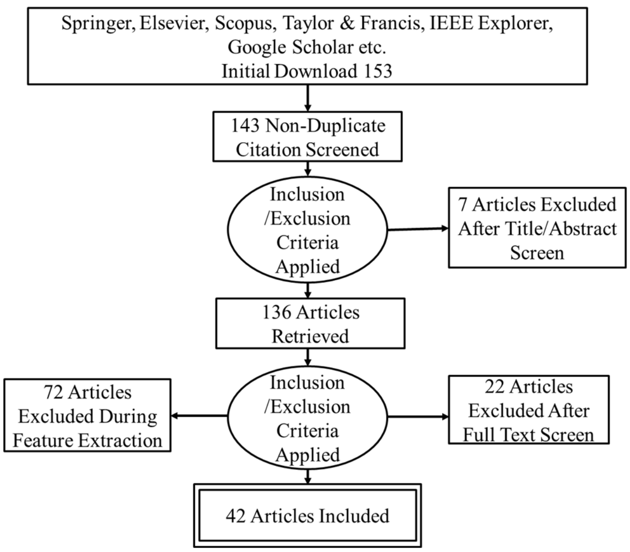

FIGURE 2. Selection of articles for feature extraction.

Directory of Open Access Journals, Association for Computing Machinery, Wiley Online Library, Inderscience, IEEE Xplore and Google Scholar. Our keyword search was guided by the approach presented in [14]. The following keywords were used in our searches: (i) AI in LCE, (ii) AI in industrial manufacturing, (iii) ML application in LCE and (v) adaptive manufacturing with AI. Figure 2 shows the study framework for selecting the relevant papers.

A total of 153 papers were downloaded; all papers were read entirely to ensure that they were within the scope of this study. Out of the 153 papers, 8 were duplicates, and 2 papers not published in English were removed, leaving 143 records shortlisted for the screening stage. Four records were found to overlap, and 3 papers (newspaper articles and webpages) were also omitted, reducing the eligible papers for our qualitative analysis to 136.

Of the 136, 22 papers (review studies on AI and ML applications in LCE) and 72 papers (AI and ML applications in fields rather than LCE) were further excluded. Consequently, 42 papers were used in the quantitative analysis of our SLR.

D. REPORTING
1) SUSTAINABLE DEVELOPMENT GOALS
The United Nations General Assembly (UN-GA) adopted the 17 SDGs in 2015 as the blueprint for achieving a better and more sustainable world for all by 2030. Countries are supposed to fulfill these 17 goals to make the world a better place to live for future generations.

2) WORD CLOUD
Word cloud is one of the visualisation techniques of text-based features of the data, where a grouping of words is displayed in various sizes. The larger and bolder the term, the more frequently it appears in a document, and the more essential it is.

We used the word cloud a few times in this paper.

3) CHORD DIAGRAM
Chord diagrams, also known as radial network diagrams, are a form of data visualisation that became quite popular because of how colourful and eye-catching they can be. They are most useful when trying to convey the relationship between different entities.

In this paper, we used one chord diagram to show the relationship between engineering activities and tasks.

III. FEATURE EXTRACTION
Several features are extracted from the selected papers for further analysis.

A. SUSTAINABLE DEVELOPMENT GOAL
The SDGs or global goals are a collection of 17 interlinked global goals designed to be a 'blueprint to achieve a better and more sustainable future for all'. We have made an effort to connect the paper's content to that of the SDG objective; for example, if a paper discusses any creative solutions employing artificial intelligence or other digital approaches in the industrial sphere, we include it in SDG 9.

According to our interpretation of the SDG's subject, the articles that were chosen primarily addressed SDGs 9, 11, and 12, which are presented in Table 1.

TABLE 1. List of SDGs (keep only 9,11, 12).

SDG No	Name of the SDG
9	Industry, Innovation and Infrastructure
11	Sustainable Cities and Communities
12	Responsible Consumption and Production

B. ENGINEERING ACTIVITY

Engineering activity is another important feature extracted in this paper to find only those engineering activities where LCE-AI technology is used. Several engineering activities, such as industrial operations, logistics, maintenance and repair, manufacturing, operation at end-user, order dispatching, packaging planning, power equipment residual life, procurement, product assembly, product design, production design, production performance, product life cycle, reuse remanufacturing and recycle and service design are investigated through the selected papers.

C. COMPANY AND COMPANY TYPES

Which company the engineering activity took place in and what type of company it was also investigated. Most of the selected articles are part of academic research in different universities; however, they highlight different industrial use cases. It was found that LCE-AI technology has been widely used in the automotive industry, battery production technology, a manufacturing company, the railcar industry, the robot and automation industry and university research.

D. AI-ML METHODS AND TASKS

The AI-ML tasks and methods have also been investigated through the selected papers. Table 2 presents a summary of the AI-ML tasks and methods.

E. KEYWORDS

Keywords are also extracted as features from the selected papers. All the keywords are then analysed using a word cloud to see which keyword is mostly used in the selected papers.

F. YEAR

The timeframe is extracted as a feature, especially in which year the selected papers are published and extracted.

G. COUNTRY

The country of the article is extracted. In this case, the country is considered based on the authors' country.

H. PUBLICATION TYPE

The publication types, such as journal, conference and workshop, are extracted as features.

TABLE 2. AI/ML tasks and methods identified in the selected papers and used in the classification process.

AI-ML Tasks	Methods
Classification	PCA, KNN, CNN, RF, LR, DT, SVM, RNN, Light-GBM, Agent-Based Model, Graph-based model
Clustering	GA
Data Analysis	Cosine similarity, TF-IDF model, k-means clustering, Autoencoder, Hybrid model
Decision Support	Fuzzy logic, Quantitative measurement method, Rough set theory, SVM
Knowledge Management	Knowledge link, Ontology
Machine Diagnostic	Knowledge-based model
Optimization	GA
Prediction	DT. Fuzzy System, CART, C4.5, NewId, Itrule, CHAID, CN2, Q-learning, RF, Monte Carlo tree search, Digital twin, Knowledge-based model, ANN, Levenberg Marquard t algorithm
Regression	ANN, GBT, SVR, PCA, KNN, CNN, LSTM, RF, RF, LR

I. TECHNOLOGY USED

The technology used for the experiment was also investigated. Most of the experiment was conducted using a local computer environment; however, few experiments were conducted in a cloud environment. Additionally, a simulation-based experiment was done in several experiments.

J. DATASETS

The dataset characteristic was another feature investigated from the selected papers.

IV. ANALYSIS AND SYNTHESIS

Table 3 presents a summary of the 42 articles.

We found 42 papers that explored AI/ML and various aspects of LCE. The above graph depicts the number of papers published in each year from 1997 to 2021. We also found the majority of them, i.e. 12 papers in 2021. As shown in Figure 3, AI/ML has been applied in LCE basically for the last 5 years and is increasing yearly.

Figure 4 shows a variety of engineering activities covered in the publications. The green ones on the left were also mentioned in the 'AI-LCE' paper [46]. In seven papers,

TABLE 3. The final 42 articles present Engineering activity, AI methods and AI tasks.

Eng_Activity	Industrial_Task	AI/ML Methods	Task	SDG	Ref
Logistics	Supply chain design	Fuzzy logic	Decision support	12	[15]
	Production planning	Inbound logistics model	Classification	9,11	[16]
	Inductive learning	DT	Machine learning	9	[17]
Maintenance and Repair	Robot fault forecasting	KNN, CNN	Classification regression	9	[18]
	Time-to-failure for aircraft engines	LSTM, RF	Regression	9	[19]
	Predictive maintenance	Light- GBM	Classification	9,12	[20]
	Predictive maintenance	Prediction of the Mean Time to Failure(MTTF)	Kurtosis analysis	9	[21]
	Digital transformation	Hybrid model	Data analysis	9	[22]
Manufacturing	Manufacturing cost molding	ANN, GBT, SVR	Regression	9	[23]
	Scheduling	RF, DT, Monte Carlo tree search	Prediction	9,12	[24]
	System disruption prediction	LR, RF, DT	Classification	9	[25]
	Decision making in manufacturing	NLP	NLP	9	[26]
Operation at End user	Life cycle analysis	Data analysis	Decision Support	9	[27]
	Automated sensory analysis	NLP	NLP	9	[28]
Others	Product lifecycle management	Knowledge Link, Ontology	Knowledge Management	12	[29]
	Predictive analytics	Cosine similarity and TF-IDF	Data analysis	12	[30]
	Technical condition assessment	DT, Fuzzy system, CART, C4.5, NewId, Itrule, CHAID, CN2	Forecasting	9,12	[31]
	Production planning	RF	Classification regression	9	[32]

TABLE 3. ***(Continued.)*** **The final 42 articles present Engineering activity, AI methods and AI tasks.**

	Knowledge-based engineering	Reinforment learning	Reinforcem ent learning	9	[33]
	Production activities performance	NLP, RF	NLP	9,12	[34]
	Digital transformation		Machine learning	9	[35]
Procurement	Machine supervisory system	RF, LR	Regression	9	[36]
Product Assembly	Adaptive action		Adaptive action	12	[37]
Product Design	Design	GA	Clustering	9,12	[38]
	Design	Clustering	Clustering	9,12	[39]
	Product lifecycle optimzation	GA	Optimizatio n	9,12	[2]
	Knowledge-Based engineering	Knowledge based	Machine diagnostic	9	[40]
	Digital twin	Digital twin, Knowledge-based system	Prediction	9	[41]
	Life cycle performance	Not found	Prediction	9	[42]
Production Design	Knowledge management	Quantitative measurement method	Decision support	9	[43]
	Economic impact analysis	SVM	Decision support	9	[44]
	Production, Scheduling, Performance	Reinforment learning	Reinforcem ent learning	9,12	[45]
	Demand forecasting	XAI with decision making AI model	Prediction	12	[46]
	Digital transformation	Not found	Prediction	12	[47]
	Cyber-physical production system	k-means clustering and autoencoder	Data analysis	12	[48]
	Business model innovation	Not found	Forecasting	9	[49]
	Adaptive LCE	SVM, k-NN, ANN	Not specified	9	[1]
Reuse/Reman/ Recycle	Smart manufacturing	SVM after using PCA, ANN(CNN & RNN)	Classificati on	12	[50]
	Decision support	Graph-based model	Classificati on	9	[51]

TABLE 3. ***(Continued.)*** **The final 42 articles present Engineering activity, AI methods and AI tasks.**

Service design	Diagnosis of machine process lifecycle	A novel deep transfer learning enabled adaptive diagnostics approach	Deep Transfer learning	9	[52]
	Agent-based modeling	Agent-based model	Classificati on	9	[53]
	Predictive model	ANN, Levenberg marquardt algorithm	Prediction	9	[54]

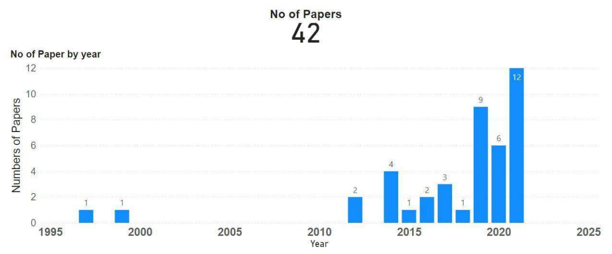

FIGURE 3. **The number of papers by year.**

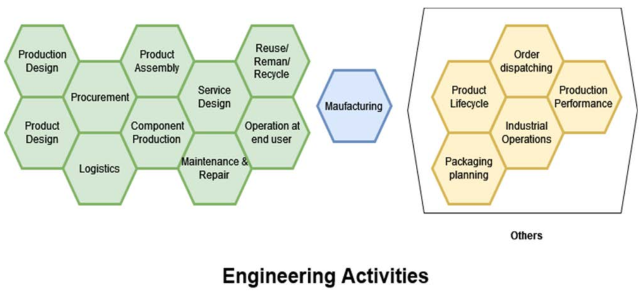

FIGURE 4. **Engineering activities.**

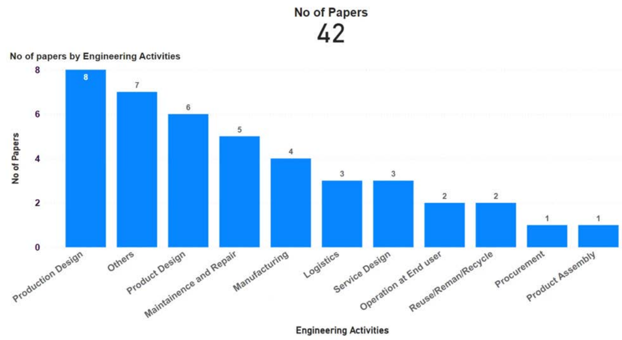

FIGURE 5. **The number of papers by Engineering activities.**

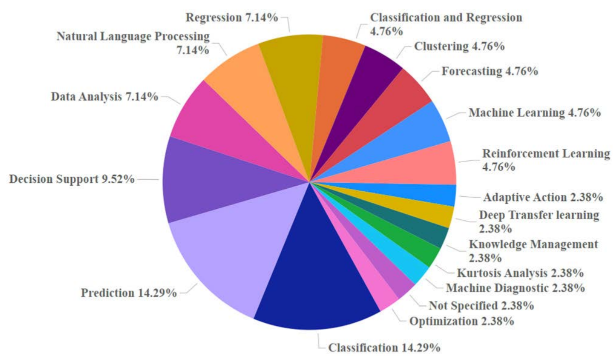

FIGURE 6. **Pie chart for AI/ML tasks identified in the papers. The size of the task represents how many papers in percentage this task was mentioned. Some papers did not specify any tasks, they are classified as 'Not Specified'(i.e., 2.38%). A paper may mention more than one task and contributes to the size of all these tasks.**

we found more categories like 'Manufacturing' and five more categories that we kept in 'Others'.

Figure 5 shows the number of papers by engineering activities.

It can be seen that most engineering activities where AI/ML is applied are production design, product design, maintenance and repair and manufacturing. It also seems that product assembly and procurement are still limited in applying AI/ML, where future LCE could be considered. However, other engineering activities in LCE, e.g. product life cycle and packaging, and performance order dispatching, are the newest engineering activities where AI/ML is increasingly applied.

Several AI/ML algorithms and their related tasks are used in LCE, as they are observed in the 42 papers. In Fig. 6 we have found, 'Prediction' and 'Classification' are the two most used AI/ML tasks in those 42 papers, both are 14.29%. From Fig 8 we see that those are 6 papers. Fig. 7 the word cloud compares the word term of the title and keywords of the papers.

We expanded AI to artificial intelligence in the word cloud but 'using' in the stop word list. We have made a list of stop words removing non-relevant keywords to give a more relevant picture of the word cloud for titles. We also expanded acronyms and merged synonyms, e.g. 'LCE' translates to the phrase 'life cycle engineering', 'life cycle' to 'lifecycle' and diagnosis to diagnostics (for full synonyms and stop words used, contact authors).

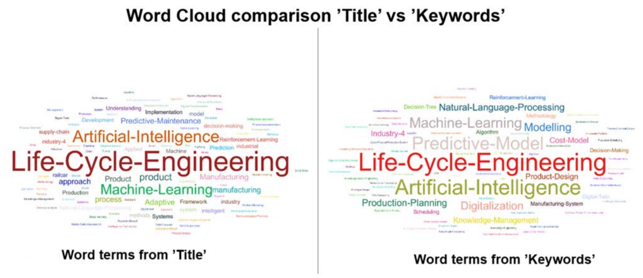

FIGURE 7. To give an intuitive image of the papers, we made a word cloud comparison between all titles and all keywords of the papers but we removed words related to the specific application and those with low significance. We added words to the stop word list that do not contain information on their own, e.g. assistant, analysis, method, replace, order, ambiguity, estimation and dispatch. We also added some words related to the application, e.g. railcar and hydrogen. We translated several specific AI and ML terms to AI or machine learning since we called them in detail in Figure 13. We used synonyms to handle stemming and words with similar meanings.

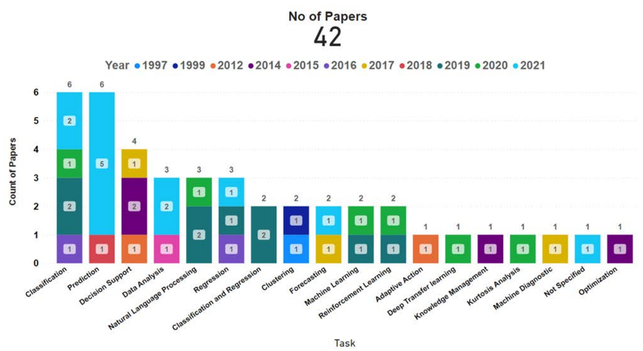

FIGURE 8. The number of papers by task (algorithms) by year. The x-axis is the total number of papers containing a specific term. The colours represent the countries of the first author.

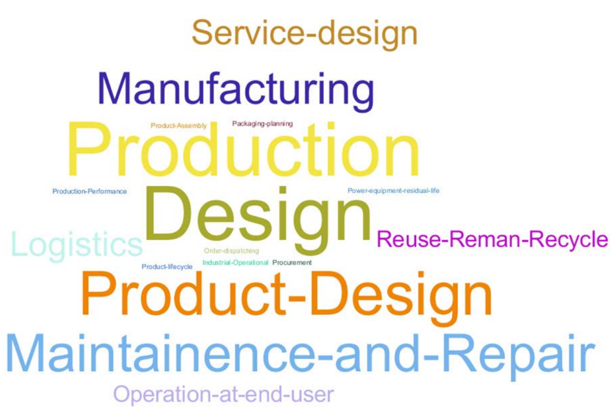

FIGURE 9. Word cloud of the task of engineering activities in LCE that we have manually identified in all the selected papers.

Figure 8 shows the number of papers per task (algorithm) for each year. It can be seen that most of the papers are from between 2016 and 2021. For example, the prediction task was applied to five papers.

Figure 9 shows the word cloud of tasks tackled by 42 papers.

TABLE 4. Selected AI - LCE papers with the first authors' affiliation.

Country	Score	Ref
Germany	9	[29], [16], [24], [18], [32], [33], [45], [48], [42]
USA	4	[50], [34], [28], [35]
UK	3	[23], [26], [41]
China	3	[43], [44], [52]
Canada	2	[38] [39]
France	2	[15], [25]
Italy	2	[2], [53]
Poland	2	[30], [40]
South Africa	2	[21], [54]
Bosnia and Herzegovnia	2	[20]
India	2	[36], [22]
Sweden	2	[1], [47]
Finland	1	[49]
Hungary	1	[37]
Japan	1	[51]
Russia	1	[31]
Slovakia	1	[27]
Slovenia	1	[46]
Spain	1	[17]
Total	42	

Table 4 shows a list of countries based on the author's workplace. Here it can be observed that most of the work is done in Europe, even in Germany. Only a few works had authors from different nations collaborating on them.

None of the 42 papers identified any specific SDG number that has been addressed by the authors. However, this study attempted to find the SDGs and connect the dots between SDGs and their solutions. For example, if they used an innovative way to solve industrial challenges, the study linked them to SDG 9. Figure 11 shows the analysis, where most of the papers are found in SDG 9, i.e. 'Industry, innovation and infrastructure.

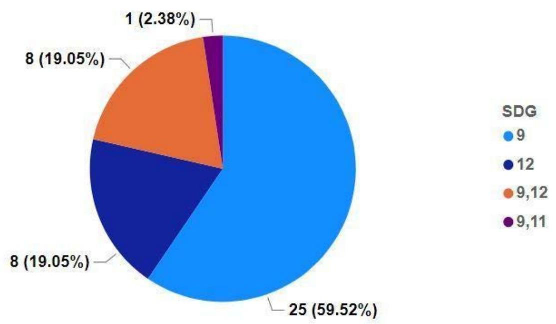

FIGURE 10. The number of papers by SDG.

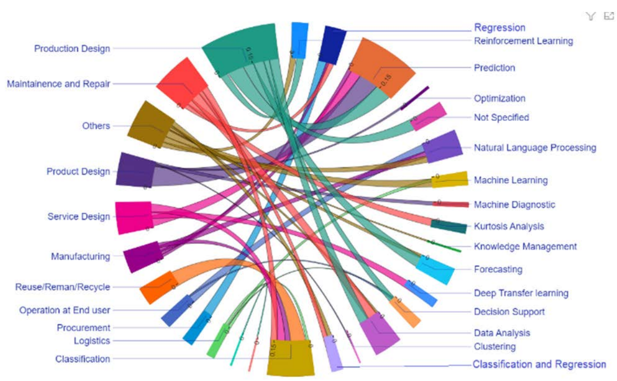

FIGURE 11. Chord diagram connecting engineering activities mentioned in the papers (on the left side of the diagram, one paper can mention more than one engineering activity; therefore, it is included in more than one engineering activity). The diagram connects the papers with the ML tasks mentioned in the paper on the right side, and one paper may mention more than one task. The engineering activity, 'Others', are engineering activities, such as order dispatching and packaging.

Why do we try to relate to it?

The goals must be achieved not just by countries but also by industry, researchers and businesses. We attempted to link the SDG with the problems that the papers addressed. Although papers are not required to specify the SDG problems they tackled, it was our objective to do so. Based on our findings, goals 9, 12, 9 and 11 and 9 and 12 are mentioned in those 42 documents.

Goals that match with these papers:

Goal 9: Industry, innovation and infrastructure promoting sustainable industrialisation, upgrading technological capabilities of the industrial sector, increased resource use efficiency and greater adoption of clean and environmentally sound technologies and industrial processes are aligned with LCE.[1]

Goal 11: *Sustainable cities and communities,* safe and affordable housing, sustainable transport system and planning and inclusive and sustainable urbanisation are discussed.[2]

[1]https://www.un.org/development/desa/disabilities/envision2030-goal9.html

[2]https://www.globalgoals.org/11-sustainable-cities-and-communities

TABLE 5. Demonstrates Fig 11 in more details.

Engineering Activities	Task	% of Grand Total by No of Papers
Logistics	Classification	1.11%
	Decision Support	0.33%
	Machine Learning	1.33%
Maintenance and Repair	Classification	2.77%
	Classification and Regression	1.88%
	Data Analysis	4.43%
	Kurtosis Analysis	2.99%
	Regression	2.21%
Manufacturin g	Classification	2.10%
	Natural Language Processing	2.55%
	Prediction	1.77%
	Regression	1.22%
Operation at End user	Decision Support	0.66%
	Natural Language Processing	3.32%
Others	Classification and Regression	1.99%
	Data Analysis	1.00%
	Forecasting	1.44%
	Knowledge Management	0.55%
	Machine Learning	3.21%
	Natural Language Processing	2.66%
	Reinforcement Learning	2.33%
Procurement	Regression	3.77%

TABLE 5. ***(Continued.)*** **Demonstrates Fig 11 in more details.**

Product Assembly	Adaptive Action	0.44%
Product Design	Clustering	0.33%
	Machine Diagnostic	1.55%
	Optimization	0.78%
	Prediction	8.31%
Production Design	Data Analysis	3.99%
	Decision Support	2.55%
	Forecasting	4.54%
	Not Specified	4.65%
	Prediction	6.98%
	Reinforcement Learning	3.10%
Reuse/Reman /Recycle	Classification	6.31%
Service Design	Classification	3.65%
	Deep Transfer learning	2.88%
	Prediction	4.32%

Goal 12: Responsible consumption and production, which targets to achieve sustainable management and efferent use of natural resources, significantly reduce the waste generation by prevention, reduction, recycling and reuse.[3]

According to goal number 9, the industry needs to upgrade the technological capabilities in the industrial sector to make the industrial process much smoother. It can be in the design, manufacturing process or other parts of the industrial product development life cycle. As technological advancement is always on the move, new technological implementations in the industrial process are necessary to fulfill goal 9. Digitisation, particularly AI, the Internet of Things and data lakes of the few that can be applied to make a sustainable industrial process.

Table 5 shows the chord diagram of Fig 11 in further depth and indicates the relationship between "Engineering Activities" and "Tasks" in terms of the number of papers. For instance, 1.11% of papers addressed issues for

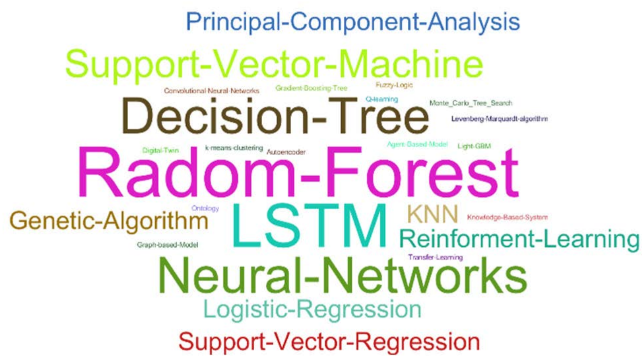

FIGURE 12. **In this word cloud, we show all the different AI/ML methods used in the selected paper. We found many different ML/AI methods mentioned in the papers to give a visual impression of which A/ML methods are most mentioned, used or discussed in the selected papers. See also Table 1 for more details.**

the logistic "Engineering Activities" with the classification "Task."

Also, it can be seen from Fig. 13 that the chord diagram represents the interrelationship between the AI/ML task and engineering activities based on the number of papers. For example, prediction tasks are used in six papers: two from production design, two from product design, one from manufacturing and one from service design, as shown in the above diagram.

Figure 12 shows the word cloud of AI/ML methods used in 42 papers, such as support vector machine (SVM), reinforcement learning and random forest (RF), to name a few.

V. DISCUSSION

This paper investigates the contributions of AI in LCE through an SLR, i.e. SLR, for the past decades. The need for a research protocol for SLR is considering transparency, transferability and replicability of the work, which are the characteristics that make a literature review systematic. This helps minimise the bias by conducting exhaustive literature searches.

Initially, 153 articles related to LCE were found in different publications, such as Springer, Elsevier, Scopus, Taylor & Francis, IEEE Xplore and Google Scholar. However, 111 articles were excluded based on the title and abstract and which are not focused on AI-LCE. This huge number of articles are out of the scope of this paper and excluded. Consequently, 42 articles were selected through the quantitative analysis of SLR methods focused on AI-LCE. The selected 42 articles to highlight the contributions of AI/ML approaches/methods/techniques in different areas of LCE. Different AI/ML algorithms have been discussed to explore the possibilities and make LCE activities more automated and smarter. To give an intuitive image, a comparison of the word cloud of titles and keywords is presented in Figure 7 of the selected articles but removed words related to the specific application and those with low significance. This figure visualises that the titles are centred on the word 'Life Cycle

[3]https://www.un.org/development/desa/disabilities/envision2030-goal12.html

Engineering', whereas other high-frequency terms are 'AI' and 'ML'. Figure 8 presents another word cloud based on the keywords of each article; however, in this case, only computer science-related keywords are considered. Figure 8 also provides a crystal-clear visualisation that the selected papers highlight more on 'LCE' and 'AI'.

Three RQs have been addressed throughout the articles, and different analyses have been conducted. To answer the RQs, 14 different features have been extracted and further analysed using different visualisation techniques, such as chord diagrams, pie charts and bar plots. Extracted features are also analysed in tabular format to understand the greater significance level of AI-LCE.

The first RQ aims to investigate the main areas where LCE is mostly dealt with. Literature shows that LCE is applied in ten different areas, including product design, production design, procurement, logistics, product assembly, component production, service design, maintenance and repair, operation at end user and reuse remanufacturing/recycling [1]. However, this paper further identifies five more areas where AI-LCE technology is used. These additional five areas are product life cycle, packaging planning, order dispatching, industrial operations and product performance, which are presented in Figure 4. Figure 5 then highlights the number of articles considering different engineering activities. Interestingly, the greatest number of articles is found for production design, whereas the lowest number of articles is found for product assembly. One of the reasons behind this can be that automation processes are applied more for production design activity than product assembly. Similar results are also found using the word cloud, which is presented in Figure 10. The analysis in Figure 13 also shows that the largest groups of papers in LCE address production design, product design and maintenance and repair.

To see the trend of AI-LCE per year, the selected articles are analysed using a bar plot (Figure 3). It is seen that AI-LCE-related articles were not published before 2014. For our investigation, only four articles are found before 2014 because AI is quietly a new era of technology that has been deployed enormously in recent years. This is visible in Figure 3 that the trend has a significant increment after 2014, which is a true reflection of AI being used in LCE.

It is also investigated to see which country/countries are the pioneers in publishing AI-LCE articles around the globe. Table 4 presents the number of articles considering the first author's country name, where the top three pioneer countries are Germany, the USA and the UK, publishing nine, four and three articles, respectively. For the bigger picture, Figure 11 then highlights that Europe is the ultimate geolocation to publish AI-LCE articles.

The second RQ investigates the AI/ML methods and tasks that are most commonly used in LCE. Table 3 highlights the overview of AI/ML methods and tasks based on engineering activity. It is observed that fuzzy logic and decision tree (DT) are used mostly for logistics, whereas deep learning method, convolutional neural networks and long short-term memory are used for maintenance. For manufacturing activity, DT and RF algorithms are mostly used. Overall, it is observed that DT, SVM, neural network (NN) and RF algorithms are the most popular methods for different engineering activities. Figure 14 presents a word cloud to provide an instinctive overview based on all AI/ML methods mentioned in the selected articles. The word cloud shows that RF, LSTM, DT and NN are bolder than other methods. We also investigated which AI/ML tasks, such as classification, clustering and prediction, are mostly used in LCE. Figure 6 presents a more vivid analysis of AI-ML tasks used in LCE. It is noted that "prediction" and "classification" have the highest proportion (14.29%), followed by "decision support" (9.52%), "data analysis," "natural language processing," and "regression" (7.14%), and so on. Figure 9 presents the number of papers by AI-ML tasks each year. It is observed that most of the papers are between 2016 and 2021 and in 2021, e.g. the prediction task was applied to six papers.

Figure 11 shows a chord diagram to emphasise which AI-ML tasks are mostly used for which engineering activities. This is an interesting observation, which helps forecast the future trend of AI in engineering activities in the industry. This chord diagram also represents the interrelationship between the AI/ML task and engineering activities based on the number of papers. For example, prediction tasks are used in six papers: two from production design, two from product design, one from manufacturing and one from service design, as shown in the diagram.

Furthermore, the third RQ emphasises 17 SDGs, and this paper investigates which SDGs are obtained most in the selected articles. From the extracted features, it is observed that only SDGs 9, 11 and 12 are achieved by the selected articles. Figure 10 shows a pie chart highlighting that 25 articles (≅25%) obtained SDG 9 and 8 articles (≅19%) obtained SDG 12. However, eight articles (19%) obtain SDGs 9 and 12, and one article obtains SDGs 9 and 11. The other SDGs are not found in the selected papers, which are not relevant to AI-LCE.

VI. CONCLUSION

This paper investigates the contributions of AI to LCE through a systematic review considering the literature of past decades. It also aims to determine the current and potential AI techniques in LCE, enhancing the study and practice of LCE. We used a specific set of inclusion and exclusion criteria to identify and examine papers from several fields: production, logistics, marketing and supply chain. Primarily 153 papers were selected and based on inclusion and exclusion criteria, 42 articles were selected as final consideration for further analysis. The inclusion and exclusion criteria included thoroughly scanning the title, abstract and application field related to LCE. This paper provides insights through systematic analysis and synthesis. It has been observed that academic papers on AI-based LCE have been increasing since 2015, and the trend is increasing. We categorized the scientific papers based on which LCE activity they addressed and which AI techniques they used. Most papers are of a technical characteristics and in the area of applied AI research. The main applications of AI in LCE are Classification, Prediction, Decision Support and Data Analysis. Looking at the findings there may be missed opportunities, and the area of AI-LCE may benefit from a more systematic approach. Using techniques such as chord diagrams, pie charts and matrices enables a visualization of what is ongoing in the research area of AI-LCE.

AI techniques used in LCE are mainly different algorithms in ML, such as NN, SVM and RF. It is also noticed that most LCE research papers are on production, manufacturing and logistics. However, in the chord diagram, we see that the largest groups of papers in LCE address production design, product design and maintenance and repair.

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