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AI-LCE: Adaptive and Intelligent Life Cycle Engineering by applying digitalization and AI methods – An emerging paradigm shift in Life Cycle Engineering

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Abstract

This paper presents a vision for a much-needed paradigm shift in Life Cycle Engineering (LCE), which is termed Adaptive and Intelligent Life Cycle Engineering (AI-LCE). To do so, interdisciplinary analysis of literature in domains of AI and LCE is performed. Needed concepts and methods are described: key enabling technologies are Artificial Intelligence (AI), the Internet of Things, and data lakes, which are becoming cost-effective and increasingly implemented in industry. Both artificial and human intelligence are used in combination. Its advantages compared with the conventional LCE include shorter time for changing activities in the lifecycle and the accuracy of changes made.

Keywords: Artificial Intelligence; Internet of Things; vision; time; accuracy

1. Introduction

Life Cycle Engineering (LCE) may be regarded as an established discipline [1], however it is currently under further development for societal challenges, such as the transition towards a circular economy [2], and thanks to newly implemented technologies such as Artificial Intelligence (AI). LCE employs the lifecycle perspective and provides a set of methodologies such as lifecycle design [1]. Several lifecycle design methods can be powerful to consider foreseeable consequences within upcoming phases (e.g., production, use, and post-use treatment) early in design [1]. A number of manufacturers have service businesses in the use phase by, for example, providing continuous maintenance [3], and such businesses often provide opportunities to get data on products in use. Moreover, many companies have a high potential to design and provide the products and services holistically as a Product/Service System (PSS) [4], which is an integrated system of products and services.

The manufacturing industry today faces the megatrend of digitalization, which involves AI (artificial intelligence), Industry 4.0, Cyber Physical System (CPS) [5], among others. Accordingly, data-driven smart manufacturing [6] is proposed, and new capabilities of designing smart products are needed for designers [7]. Some advanced cases with documented potential are found in literature: e.g., smart techniques were applied to make prioritization of maintenance activities, which resulted in cost minimization [8].

The major missing knowledge is, however, what value, in general, can be created and captured out of data in the whole lifecycle [9]. Also, the great challenge is that the value creation and capture need to be designed and managed from a holistic lifecycle perspective by avoiding sub-optimization (e.g., optimization of energy use in a factory). Research applying AI

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to the sustainability issues in real-world cases is limited, though there are a few exceptions (e.g., [10]). The application of AI and the assessment of its implications with the lifecycle perspective are among the major missing scientific insights [11]. Filling the knowledge gaps will guide the manufacturing industry to exploit the potential of AI.

This paper, given the opportunity with these gaps, presents a vision and concepts for an emerging paradigm of LCE, termed Adaptive and Intelligent Life Cycle Engineering (AI-LCE). Literature review and analysis is adopted as the research method. This proposed, new way of engineering adapts the activities throughout the lifecycle such as design, logistics, production, maintenance, repair, and remanufacturing by collecting and using data from the lifecycle as well as applying AI methods and techniques. The major advantage lies in its adaptability: the time needed to adjust and change activities either reactively or proactively is significantly shorter than with the current practice of LCE, as needed adjustments are implemented directly within the current product lifecycle or even in real time. Also, the accuracy of the changes made is increased for the relevant actors. The major advantage lies in highly effective problem identification from the lifecycle perspective and efficient problem solving through suitable AI methods and techniques.

The remainder of this paper is structured as follows: Section 2 describes the state of the art and research gaps in LCE and AI specifically. Section 3 then presents the vision and its related concepts. Finally, Sections 4 and 5 provides the discussions and implications and concludes the paper, respectively.

2. State of the art and research gaps

An improvement potential is found for feedback loops from product quality to improve the manufacturing process and system management in industry according to Lee et al. [12]. Gopalakrishnan [13] states that current maintenance decisions are rarely fact based, and Garg et al. [14] assert that much of the Computerized Maintenance Management System (CMMS) data are rarely analyzed to be used for coordination or decision support. Labib [15] also states that commercially available CMMS software lacks decision analysis support for management. One major issue with the data in, for instance, CMMS is that it is often of free-text character and thus analyzed manually, which both consumes resources and takes time [16]. Further, it is recognized that a systematic approach to and integration of AI is needed before the real impact of Industry 4.0 can be harvested [17]. Such a systematic approach would assist decision-making not only within maintenance and quality improvement within operations but within the entire lifecycle (e.g., design procurement, production design, manufacturing/assembly, operations, service, reuse, remanufacturing and recycling).

In relation to AI and digitalization, new concepts and techniques have also been recently proposed, for example, deep learning [18], cloud manufacturing [19], and data-driven smart manufacturing [6]. Furthermore, the importance of data-driven decision making on a digital business strategy and in the industrial domain is highlighted by [20]. According to the literature, decision-support and knowledge-based systems based on data-driven methodologies are being developed using different Machine Learning (ML) methods, for example, Support Vector Machines (SVM), fuzzy logic, clustering, deep learning, k-Nearest Neighbour (kNN), dynamic Bayesian networks, Artificial Neural Networks (ANN) and hidden Markov models [21-23]. The predictive maintenance (PdM) 4.0 [24] approach uses data analytics and ML techniques to predict failures at a high level of accuracy, enabling self-awareness of technical health. The literature also shows that PdM based on ML is gaining interest from the industry sector (Table 1) [25, 26]; Table 1 presents recent advancement of AI and ML algorithms in manufacturing industries.

Research applying and integrating AI with sustainability issues is, however, limited thus far with a few exceptions including the application of a genetic algorithm support vector machine multiple kernel learning to improve efficiency in smart electricity grids [10]. The potential impact of lifecycle data on resource efficiency and effectiveness has been highlighted, for example, when it comes to insight gathered by service technicians and its impact activities both upstream (design) and downstream (remanufacturing) in the lifecycle [27, 28]. While prior research further indicates the potential positive impacts of the utilization of lifecycle data on resource efficiency and effectiveness, its utilization still poses a challenge for businesses designing and providing PSSs [29]. Furthermore, most of these AI techniques have hardly been systematically applied to reduce, solve, or prevent real-world problems from a lifecycle perspective. The application of AI and the assessment of its implications are among the major missing insights. The

Table 1. List of AI and ML algorithms in manufacturing industries .

Year	References	Goal	Method
2019	[30] [31]	Predictive maintenance	Support Vector Machines (SVM) and Artificial Neural Networks (ANN)
2019	[32]	Anomaly detection	Autoencoder and Extreme learning machines
2019	[33]	Predictive maintenance	Unsupervised clustering algorithm and a pattern recognition neural network
2019	[34]	Predictive maintenance	Chronicle mining and neural network
2018	[31]	Fault detection	Principal Component Analysis (PCA), Hotelling's T-squared distribution (T2 statistics), K-means, Hierarchical clustering, Fuzzy C-Means clustering and Model-based clustering
2018	[35]	Predictive maintenance	Generalized linear models, Random forest, Gradient boosting machine and Deep learning
2017	[36]	Classify defect	Multilayer perceptron (MLP)
2017	[37]	Tool wear Prediction	Random Forest (RFs), Feed-Forward Back Propagation (FFBP) neural networks, Artificial Neural Networks (ANN), Support Vector Regression (SVR)
2017	[38]	Predicting potential failure	Auto Regressive Integrated Moving Average
2017	[39]	Predictive maintenance	Random forest algorithm
2017	[40]	Predictive maintenance	Classification, Support Vector Machines (SVM) based regression and clustering
2017	[25]	Predictive maintenance	Linear regression, Logistic regression, Neural networks, Decision trees, Random forests, Gradient boosting machines,

authors have applied AI methods and techniques to improve production for specific applications, such as fault diagnosis, process adjustment and monitoring, and these have proven to be feasible and successful; for some examples, see [41-44]. However, these are not enough to make a breakthrough for using AI in LCE; these are more "one-shot" successful applications, but not leading to the systematic use of AI in the full lifecycle of products.

3. Vision, concepts, and methods

3.1. Vision

A large number of traditional engineering activities for the environmental aspect in practice are often associated with a weak or non-explicit connection between different phases (such as improving energy efficiency in a machining process or a factory). Thus, there is an ongoing risk of sub-optimization. One reason for this may be the way of looking at or addressing engineering as a number of activities and processes in a sequence or independently. By lifting up the perspective to a highly integrated collaborative view that is coordinated by business intelligence (e.g., [45]) with the support of global memory, the focus can be shifted from sub-optimization to optimizing the complete lifecycle. This shift is considered as a natural step seen from the Industry 4.0 perspective where digitalization in a factory (e.g., intelligent production systems [46]) is the first step, followed by the global intelligence and optimization step.

Our vision is to advance existing LCE towards more dynamic engineering that enables continuous and flexible improvement and optimization on all levels. Information from all corners of the lifecycle together with external factors (from end user, environment, economic aspects, etc.) are used to improve the product lifecycle, as depicted by Fig. 1. This new way of LCE is composed of a number of already-existing activities such as design, production, and maintenance. However, these activities will not necessarily be arranged in a sequence but coordinate and, if needed, interfere with whichever activity is relevant. This is realized by business intelligence: for example, ordering the right numbers for new production and remanufacturing based on the quality conditions of products (cores) that are coming back to a factory after use and the current or upcoming supply of components. Key enabling technologies are digitalizing activities in each element, communicating data, information, and experience within and between the elements using, for example, the Internet of Things (IoT), and analyzing data to derive useful information and insights with AI. These technologies realize interrelations between and among the activities with a shorter time to respond and higher accuracy in information, which increases the relevance of the systems perspective on the related activities. As feedback and its time delays are among the central features of a system in general, business intelligence giving feedback plays a paramount role. This enables dynamic, holistic life cycle engineering that continuously and flexibly improves and evolves. Based on the discussion above, this new way of LCE is termed adaptive and intelligent LCE (AI-LCE).

3.2. Concepts

Table 2 lists some of the properties for AI-LCE and traditional LCE. While both have the lifecycle perspective, AI-LCE offers a number of benefits. Essential technologies for the vision are data storage, communication (e.g., IoT), and integration and reasoning.

Table 2. Comparison between traditional LCE and AI-LCE.

	Traditional LCE	AI-LCE
Perspective	Lifecycle perspective	Lifecycle perspective
Digitalization and IoT	Beneficial but not required	A foundation for deployment
Time for changing activities	Typically, longer than a lifecycle	Within a lifecycle (even on real time)
Accuracy of changes made	Low	High
Intelligence used	Mainly human intelligence	Human and artificial intelligence (complementary)
Data storage used	Local databases	Uniform data access (e.g., data lake)

By adopting the emerging concept of data lakes, we see a number of benefits such as transparency with retained confidentiality and integrity of the data and information collected and stored. In AI-LCE, data will not be stored only when its usage is predefined; data will be stored also to enable integrating new AI applications when available and when they add value. In previous projects by the authors, a lack of relevant data was found to be one major obstacle to implement AI in the lifecycle. By stepping away from a normal database approach where data is structured and stored locally for a specific purpose (and if no specific application requests it, it is not stored), we open up the possibility to continuously add more and more AI functionality (AI modules), producing feedback and improving the overall lifecycle in all stages. Data lakes separate structures from data, which enables structuring data in different ways to match the users (optimization or AI modules), and access permissions and confidentially can be handled more efficiently. Traditionally, data is structured in tables and such formats that optimize the use by some particular module, which often makes the data difficult to be used beyond the intended use. This limits its use by e.g., AI modules.

The data lake concept also enables accessible-for-business intelligence functionality of both real-time data and historical data to be used for analysis and improvement on all levels of LCE. The transparency of data increases, since the data in a data lake is associated with a description enabling other users to use the data in different ways; on the other hand, locally stored or cloud stored data is often defined in a way limiting how the data is used. Managing vast amounts of data collected during all life cycle phases and making it available, for example, for monitoring, advanced AI, and statistics, we see the emerging concept of data lakes as one potential solution. A data lake stores all enterprise lifecycle data (enabling uniform access/distribution): raw copies of source data; historical visualization, advanced analytics, and AI [47], enabling seamless information flows across aligned sub-systems and business intelligence. A data lake may also keep sensitive data

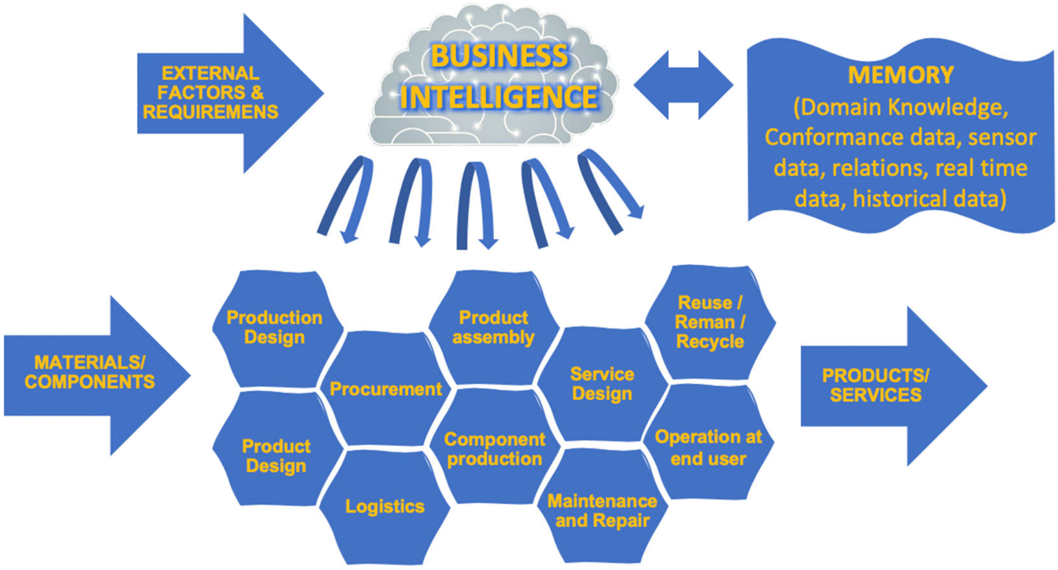

Fig. 1. Vision of AI-LCE enabling a high level of flexibility, continuous improvement, and an evolving lifecycle.

Note: External factors and requirements may be market, ethical, social and environmental requirements as well as company policies etc. Materials/components include what is needed for producing the desired output (products and services) and every hexagon has a required input and delivers an output used by other hexagons to deliver the overall products and services. The hexagons refer to engineering activities: they are performed dynamically depending on the situations, which is only symbolized in the picture since dependencies between the hexagons are highly interwoven in reality. The business intelligence is focusing on both optimization of the total lifecycle as well as optimizing every lifecycle phase, both in a short and long-term time perspective. The engineering activities give inputs to and receive outputs from the business intelligence, which exchanges information with the memory.

securely in house and only share portions of the data selectively with different users, e.g. AI functionality. Furthermore, a data lake requires discipline in giving all data clear meanings so as to be accessed and used by other modules, functions and systems, which is the main added value of a data lake.

3.3. Methods for AI-LCE

The needed methods will be developed by applying various techniques in a hybrid approach from AI (including machine learning and Natural Language Processing (NLP)), data modelling, and domain knowledge from engineering and management. Here, problem and solution ontologies will be developed to define relations between key terms. NLP will be used to identify key terms in problem and solution descriptions and Case-Based Reasoning (CBR) to identify similar problem-solution patterns to given problems. The AI solution may be installed as a multi-domain solution, domain-specific, or even within a company, allowing the provision of specific knowledge and protecting it. As a baseline, it will first provide general solutions to this domain problems without taking time constraints into account. Specifically, ML approaches, like support vector machines and neural networks, will be used to solve problems like forecast or decision support. Clustering approaches based on variations of *k*-means and spectral methods will be developed to enable data grouping according to their similarity. This will be used for different purposes, for example, to enable grouping the most similar consumers as an enabler for the application of demand response schemes. A general CBR approach will be developed in a way that it may be used to solve multiple, different problems. Finally, semantic knowledge (ontologies) will be developed to support the AI system's and solution's interoperability. AI techniques are essential to dynamically identify correlations and patterns between data of different lifecycle phases and enable continuous improvements and optimization.

4. Discussions and implications

4.1. Potential

A report by McKinsey [48], as an example, states the followings: Better predictive maintenance can reduce equipment downtime by up to 50% and reduce equipment capital investment by 3 to 5%. Improved operations can reduce maintenance costs by 5 to 10% and increase output by 3 to 5% by avoiding unplanned outages. In manufacturing, these savings have a potential economic impact of nearly $630 billion per year in 2025. Adding the effects by improvement with the more holistic view involving multiple lifecycle phases, the potential of AI-LCE will be substantial.

4.2. Technical feasibility

By using AI techniques and methods together with domain knowledge, the proposed approach enables the discovery of anomalies, analyze their consequences, and suggests solutions for how to amend them. A number of suitable AI techniques and methods will be selected and applied to available data as a proof of concept. The challenge is to both adapt and develop new techniques and methods suitable for specific challenges at hand and available data. Self-learning algorithms, still conforming to the pre-defined rules, will also cover the situations that lie outside these rules. Instead, ML methods can train algorithms. The training can be performed through simulated environment data, field testing, and operational data.

Thus, knowledge representation (deductive learning) and inductive machine learning will complement each other. ML in knowledge graphs has evolved recently as a class of mature techniques to combine rule-based systems and data mining. Machine Learning as a Service (MLaaS) is a definition of various cloud-based platforms that cover most infrastructure issues such as *data pre-processing*, *model training*, and *model evaluation*, with further prediction. These resultant models or algorithms will communicate via REpresentational State Transfer (REST) [49], that is, RESTful Web services into the demanded platforms. Amazon Machine Learning services, Azure Machine Learning, Google Cloud AI, and IBM Watson are regarded as four leading cloud MLaaS services that allow for fast model training and deployment [50]. Currently, the APIs from these four vendors can be broadly divided into three large groups:

- Text recognition, translation, and textual analysis,
- Image and video recognition and related analysis, and
- Other, that includes specific uncategorized services.

4.3. Readiness and business feasibility

A high level of digitalization is a prerequisite for moving towards AI-LCE. The different techniques and methods in both AI, digitalization, and LCE are all available, so AI-LCE is a matter of taking the traditional LCE to a new level by integrating it in the current digitalization, providing concepts, methods, tools, mechanisms, and uniform data storage/access. AI-LCE would also enable a solution to the challenge with integrity and data safety when using external platforms and external data storage. The external storage, e.g., RESTful Web services, as discussed above in the technical feasibility is not acceptable in all industrial enterprises since access to this data by competition, customer, subcontractors, and the public may cause great damage.

4.4. Impacts

Applying a dynamic, holistic LCE approach that enables continuous and flexible improvement gives LCE a means to more effectively optimize the whole lifecycle and deploy improvements faster, both on a detailed level and on the grand scale of the product lifecycle. By enabling continuous improvements, new releases of products and services are more of a marketing aspect. There is also a trend towards continuous improvements appreciated by customers, which is also an advantage from a sustainability perspective and in reducing the need for selling new products from a profit perspective and shifting the focus to selling improvements and new functionality to existing customers as well as new customers. Tesla may be seen as such an example; it sells the same car model for many years, but all aspects of the lifecycle are continuously improved, and new services and performance enhancements are released and offered to both new and existing customers.

One benefit of this approach, from an environmental perspective, is that it is easier to get an overview of the total lifecycle and also identify where investments in environmental improvements have the biggest effect. It most likely will also reduce sub-optimization, where an environmental improvement in one phase causes more negative environmental impact in other phases. Ways to reduce overall environmental impact in forms of energy use, resource use, and emissions will be easier to identify with AI-LCE since the effects of a local change can be assessed and evaluated from the overall lifecycle perspective.

5. Concluding remarks

This paper presented a vision with the needed concepts and methods for an emerging paradigm of life cycle engineering, which is termed AI-LCE. This new way of engineering adapts the activities throughout the lifecycle by intelligently collecting and using data from the lifecycle as well as applying AI methods. The major advancement lies in the time needed for and the accuracy in actions. AI-LCE has a potential to enhance both environmental and economic performance as well as value creation throughout the lifecycle. This much needed expansion of LCE is developed by employing the state of the art from multiple disciplines in a holistic and fully integrated lifecycle approach. Numerous application areas are expected: for instance, issues caused by deviations in production may be promptly captured for required changes to be implemented back in design directly within the same generation. Also, causes identified in repair may be feedback to redesign services to avoid similar problems from occurring.

The authors, taking advantage of their knowledge and experience in LCE and AI, have just begun tackling this grand challenge into AI-LCE. This research will be further carried out in close collaboration with manufacturers and AI solution providers. Real data from different phases in the lifecycle will be collected from the participating companies and used as the foundation for showing the proof of concept.

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