Integration of Artificial Intelligence and Life Cycle Assessment Methods

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Abstract. Artificial Intelligence (AI) techniques support environmental tools based on the growing availability of data and information, aligning the concepts of data modeling and analysis. The Life Cycle Assessment (LCA) is an environmental tool that requires a large volume of data to measure the performance of a product and to simulate the proposed scenarios to improve its performance. This research reviewed studies using AI techniques and their intersection with LCA from data mining. This study identified some AI techniques used in LCA studies. However, there is a lack of LCA literature using AI techniques, despite the benefits of integrated modeling. The results show that different AI algorithms are used to build LCA models. The AI algorithms of the studies act from the identification of the problem to the solution stage, therefore the integration between AI and LCA makes it possible to build predictive models of machine learning to enable assertiveness in decision making.

Keywords: Artificial Intelligence (AI), Life Cycle Assessment (LCA), Integrated Assessment Models.

1. Introduction
Currently, the growing environmental problem has caused the awakening of the sustainable awareness of society and provided a greater movement in the effort to guarantee harmony between the economy growth and environmental conservation. In this context, sustainable development plays an important role in the balance between society's demands and the preservation of natural resources[18]. The predominant socioeconomic development model worldwide puts environmental sustainability at risk, therefore science-based policy is required to support a societal transformation towards a sustainable well-being. Different methods are used to support decision making towards environmental sustainability, such as Life Cycle Thinking (LCT) and Life Cycle Assessment (LCA) [10]. LCA measures the environmental performance (aspects and impacts) of products and processes [9], supporting the identification of optimization opportunities. LCA is used as an environmental management tool that supports the understanding and quantification of the environmental performance related to different production and consumption systems for comparative and improvement purposes [7]. However, LCA studies are data intensive. The inventory analysis is the most laborious phase in LCA due to data collection and treatment that are time-consuming. Despite the increasing availability of data and information to date, the available data requires collection and treatment before using in
such studies. Hence, a combination of methods enables a synergic evaluation with more robust results, such as the integrated assessment models (IAM), increasing the assertiveness in decision making. Data science is an emerging research field that contributes to synthesizing current theories and models to integrate data collection, analysis and decision making. The amount of data and information processed daily in commercial transactions, logistics, sensors, social networks, users and analysis tools can be optimized by Artificial Intelligence (AI) systems. AI collects accurate and valuable information, analyze data, perform tasks and solve problems. The use of AI contributes to problem-solving in different areas of society, especially those regarding environmental issues such as real-time monitoring, environmental impact accounting, environmental mapping, parameter estimation and scenario simulation, providing useful information for decision making. However, the user community needs to understand the AI techniques in data science and form a comprehensive view of what can be done from these techniques in a specific context to make useful applications. LCA studies can be integrated with AI techniques to diagnose potential failures in data modeling and analysis, however, there is a lack of literature combining these methods. Therefore, this research reviewed studies using AI techniques and its intersection with LCA from data mining.

2. Materials and methods
A classic data mining approach was used to search the relevant articles regarding AI and LCA in the literature, considering three stages as shown in figure 1.

![Figure 1. Data mining steps used in AI and LCA literature searching.](image)

The Search and word processing stage considered the insertion of the keywords (Life Cycle Assessment (LCA) and Artificial Intelligence (AI)) in the searching engine of the available databases. Thereafter, the articles found were grouped in two categories: related articles (A); and others (B). In the Identification of attributes stage, two sets of keywords were defined as attributes, based on their frequency and meaning, and chosen as a centroid for mining. The sets of keywords were the following: Methods, Data Base and Impact Category in LCA; and Techniques and Application in AI. The articles were selected from semantic similarities of the defined centroids and the keywords of each article found. The selected articles were grouped and used as a reference for this work.

3. Results and Discussion
The main characteristics of AI techniques used in LCA studies are presented in Table 1.

Table 1. Main characteristics of Artificial Intelligence (AI) techniques used in Life Cycle Assessment (LCA) studies.

| Studies | Types of technologies | Characteristics | Advantages | Limitations |
|---------|----------------------|-----------------|------------|-------------|

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| Studies | Types of AI technologies | Characteristics | Advantages | Limitations |
|---------|-------------------------|----------------|------------|-------------|
| Komly et al. (2012); Ghnimi et al. (2018), | Multilayer perceptron neural network (MLP NN) | - Supervised learning - Back-propagation algorithm is widely used as training algorithm | - Easy to implement - High accuracy and consistent estimations when changes occur | - Slow speed of convergence - Numbers of hidden neurons always based on trial and error |
| Komly et al. (2016); [8] | Radial basis function neural network (RBFNN) | - Basis function used can be Gaussian or wavelets - Universal approximation | - High tolerance of noise - Fast training - Good capability in generalization | - Large number of hidden neurons needed |
| [1][7] Support vector machine (SVM) | | - Use quadratic programming to solve support vector | - Small data required - Global searching ability - High robustness against noise | - Large memory requirement and CPU time when trained in batch mode - Computational heaviness |
| [2][22] Geneticalgorithm (GA) mechanism of biological | - Selection and genetic evolution theory - Universal approximation - Heuristic algorithm | - Efficient nonlinear approximation - Short learning time - Fast in reaching optimum results | - Optimum structures are based on trial and error |
| [7][15] Fuzzy neural network (FNN) | - Human-like reasoning - Suitable for advanced control systems | - If-then rules easy to interpret - Implementation can be either from input to output or output to input - Able to accurately describe imprecise values of parameters | - Low computational time - Low robustness against noisy data |
| [11][21] Adaptive network-based fuzzy inference system (ANFIS) | - Consist of antecedent and conclusion - Integrate gradient descent method and least square method to train parameters | - Efficient nonlinear approximation - Short learning time - Fast in reaching optimum results | |
| [17][24] Artificial neural network coupled with genetic algorithm (GA-ANN) | - Predicted output value of neural network can be used as the fitness function of GA | - Prevent local minimum - Fast convergence - High accuracy | - Computational heaviness - Unable to determine numbers of hidden neurons |

All the algorithms of the presented studies (Table 1) act from the identification of the problem to the solution stage. However, most consulted articles point out that it is important that the researcher
identifies the different data sources available and fully understands what types of data can be found in each source. Besides, the data should be thoroughly evaluated and proved that they are suited to the study proposal in the stage previous to the model development. The predictive model should be fitted to the input data to make accurate predictions, avoiding underfitting (when there is a lack of data) or overfitting (when there is an excess of data) that affects the quality of the results.

The AI techniques provide a high capacity to solve complex problems with uncertain, interactive and dynamic characteristics in an economical and efficient manner. The AI methods combined with LCA were applied in studies of agriculture, climate and engineering as presented by the works of [2][11][15]. 80% of the selected articles combined AI and LCA in industrial activities (Table 1), while 10% of the studies were in agricultural activities regarding the energy and water performances. AI techniques were used to automate the LCA models and improve the quality of the inventory (Table 1), maintaining low uncertainty levels.

4. Future gaps and opportunities
LCA studies rely on generic databases in the absence of specific ones due to time and cost constraints, which increases the uncertainty of the results, while AI techniques can provide missing and unavailable information. The inventory analysis presented by the articles in table 01 was computerized and AI techniques were applied to store, track missing data, estimate and calculate potential impacts using the developed models. Zidonien et al [24] and Nabavi-Pelesaraei et al. [17] point out that the integration between AI and LCA enables the construction of predictive models of machine learning to improve the assertiveness of decision making within organizational processes [17][24]. In addition, the integrated assessment using AI and LCA methods can increase the robustness of the model and efficacy in decision making. Nevertheless, AI algorithms should be used at scale and tested in a wide variety of techniques and industrial sectors to increase its reliability.

5. Conclusion
This study analyzed the integration of Artificial Intelligence (AI) and Life Cycle Assessment (LCA) methods from literature review using data mining. AI techniques support data collection in LCA studies, however there is a lack in the literature regarding the combination of these methods in an integrated model. Thus, this study identified some AI techniques, considering key advantages and limitations, in order to support its use in LCA studies.

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