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ARTIFICIAL AND COMPUTATIONAL INTELLIGENCE

Environmental analysis of a product manufactured with the use of an additive technology – AI-based vs. traditional approaches

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Abstract. This paper attempts to conduct a comparative life cycle environmental analysis of alternative versions of a product that was manufactured with the use of additive technologies. The aim of the paper was to compare the environmental assessment of an additive-manufactured product using two approaches: a traditional one, based on the use of SimaPro software, and the authors' own concept of a newly developed artificial intelligence (AI) based approach. The structure of the product was identical and the research experiments consisted in changing the materials used in additive manufacturing (from polylactic acid (PLA) to acrylonitrile butadiene styrene (ABS)). The effects of these changes on the environmental factors were observed and a direct comparison of the effects in the different factors was made. SimaPro software with implemented databases was used for the analysis. Missing information on the environmental impact of additive manufacturing of PLA and ABS parts was taken from the literature for the purpose of the study. The novelty of the work lies in the results of a developing concurrent approach based on AI. The results showed that the artificial intelligence approach can be an effective way to analyze life cycle assessment (LCA) even in such complex cases as a 3D printed medical exoskeleton. This approach, which is becoming increasingly useful as the complexity of manufactured products increases, will be developed in future studies.

Key words: additive manufacturing; eco-design; life cycle assessment (LCA); artificial intelligence; neural networks model.

1. INTRODUCTION

Environmental protection is becoming one of the most important assets in the world. Air pollution contributes to loss of health in many people. Reduction of air pollution can save millions of lives [1, 2]. Innovative technologies, such as 3D scanning, additive printing, and reverse engineering, integrated into the Industry 4.0 paradigm, can negatively affect the environment. Innovative technologies are also increasingly used in medicine. An example is the use of additive technologies in the design and manufacturing of assistive devices, such as e.g. exoskeletons. About 15% of the world's population suffer from various types of disabilities, of which 110–190 million are persons with reduced mobility, who require the support of equipment in daily activities [2, 3]. Each assistive device must be adapted to individual needs of its user. To meet this demand, there is a strong need for flexible manufacturing processes. Additive manufacturing provides this level of flexibility – each product can have a unique design. Considering some undeniable advantages, such as the short and simple manufacturing process and relatively low manufacturing costs depending primarily on the quantity of material used, additive technologies are expected to keep gaining in popularity. A CAD model developed in an additive technology becomes a sufficient basis for the end product. The time- and labor-consuming preparations required to manufacture a product in a traditional technology are circumvented here. The soaring popularity of additive technologies is bound to increase their environmental footprint. Key issues here are manufacturing waste, end-of-life product recycling, use of non-renewable resources, emissions in the manufacturing process, and energy consumption. In order to curb the environmental impact, the size of the problem must be examined and preventive measures must follow. The aim of the paper was to compare the environmental assessment of an additive-manufactured product using two approaches: a traditional one, based on the use of SimaPro software, and the authors' own concept of a newly developed artificial intelligence (AI) based approach. Using both approaches, the authors investigated how the material used in the manufacturing process influences the environmental parameters of the product and then compared the results obtained using the two approaches. The AI-based solution is novel and has no equivalent in the literature. It fits into the concepts of computerization and the use of advanced machine learning (ML) techniques to improve manufacturing efficiency, data analysis, inference and prediction from data.

The article is structured as follows: the paper begins with a comparison of sustainable manufacturing with additive technologies, followed by a presentation of the LCA analysis and the IT tools that support this analysis. In the subsequent sections of the paper, we verify the results obtained by AI with

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traditional LCA methods (SimaPro), as the paper focuses on the development of a new method. The paper concludes with a discussion and conclusions, comparing our results with those of other authors, pointing out limitations and directions for further development, and providing a basis for replication of our research and further studies developing our concepts.

2. SUSTAINABLE MANUFACTURING VS. ADDITIVE TECHNOLOGIES

Accelerated development of Industry 4.0 brings about a number of environmental threats, such as increasing demand for electrical energy [4] and emissions of harmful compounds, to mention just a few. Electrical energy is required to operate machines and meet the growing demand for hardware computing power. Innovative solutions introduced under the Industry 4.0 framework, such as e.g. 3D printing, generate emissions of harmful substances. 3D printers use electrical energy to melt the working material. The environmental impact depends on the energy source. It is negligible with solar energy, but increases with the use of energy from the mains supply, depending on the combination of energy sources engaged by the supplier. In order to minimize the negative environmental impact of, inter alia, new technologies, in 2015 the World Commission on Environment and Development [5] defined 17 sustainable development goals and 169 targets. Aimed to help implement the sustainable development policy, they are accompanied by the concept of sustainable manufacturing, defined as the creation of manufactured products that use processes which minimize negative environmental impacts, conserve energy and natural resources, are safe for employees, communities, and consumers, and also economically sound [6–8].

Sustainable manufacturing encompasses not only manufacturing, but also preparatory and post-manufacturing processes, such as designing, procurement of raw materials, distribution, use and reuse of the product. One cannot overestimate the importance of the design process, when decisions are made concerning recyclability of the product, minimization of dangerous substances, and use of environmentally friendly materials. At the stage of procurement of raw materials, the supply chain should be considered and eco-efficient supplies secured. Manufacturing processes should generate zero emissions and provide for efficient use of resources, including electrical energy. In compliance with the sustainable manufacturing policy, distribution should include product returns, reuse and recycling. While in use by the end consumer, a sustainable product should be reliable while generating low operating expenses and zero emissions. The last stage is end-of-life disposal, with various possibilities, such as reuse, disassembly, and landfill disposal at a low cost [9–12].

For an additive technology to be considered environmentally friendly, it should feature all of the above-mentioned qualities of sustainable manufacturing. No product has been produced so far which would fully comply with the requirements of sustainable manufacturing. The key issue are emissions of contaminants, depending primarily on the type of material used. Gases and particles emitted during 3D printing contaminate the air [13, 14]. Some of them, such as those emitted by bisphenol A (BPA), used as a plasticizer and antioxidant, are presumed to have carcinogenic potential for humans [15]. Various measures are recommended to mitigate the hazards, such as use of low-emission materials and low temperatures, installing shields with filters around the printer, and monitoring emissions on an ongoing basis. Wojtyła has established that when used in 3D printing, polylactic acid (PLA) is distinctly less toxic than acrylonitrile butadiene styrene (ABS) [16]. In an environmental analysis of ankle foot orthoses, Górski [17] has found out, on the basis of the calculated carbon footprint, that a 3D-printed orthosis is much more environmentally friendly than one made in the conventional technology of plaster cast covered manually with layers of resin and fiberglass fabric [18]. In CO2eg, the carbon footprint of a traditionally manufactured orthosis is three times that of a 3D-printed one.

A study of a 3D printer working in the fused deposition modelling (FDM) technology has shown that when diverse materials and various extrusion temperatures are used, emissions of super-micron particles go down to zero and give way to emissions of ultrafine (10–30 nm) particles. Emissions increase in line with the increase in the temperature of extrusion. What is more, even a relatively short, 40-minute 3D printing cycle generates up to 200 mm^2 of emissions [19]. Steinle [20] has found that emissions of ultrafine aerosol (UFA) are much higher when printing in PLA than ABS.

A longer duty cycle of the 3D printer causes the emission rating to rise even further. What is important, 3D printing in spacious, well-ventilated rooms does not increase the UFA concentration significantly, as compared to printing in a confined, non-ventilated room. This is an important hint when choosing a room for a 3D printing laboratory. Other materials used in 3D printing are thermosetting photopolymers, which can be reused as materials reforming 3D printed objects into a new shape. The technology is used for repairing damaged parts [21].

As is the case with many other manufacturing technologies, the environmental impact of 3D printing depends largely on choices made by the user. Model design, energy source, materials in use, recyclability – all these factors determine the resulting environmental impact of the product.

Life cycle assessment (LCA) is just one of many tools facilitating assessment of the environmental impact, including those based on artificial intelligence (AI). Owing to a standardized analysis process and incorporation of numerous standards, the method ensures comparable results of analyses conducted in enterprises and research organizations, and facilitates the creation of a hierarchy of many issues related to the environmental impact of manufacturing processes and product life cycle.

3. LIFE CYCLE ASSESSMENT

Life cycle assessment (LCA) is defined in the ISO 14040:2006 standard as an environmental management technique aimed at the assessment of products, materials, processes, services and systems in terms of their impact on the natural environment. LCA covers potential impact on the ecosystem throughout the product life cycle ("from cradle to grave"), i.e. from the procurement of raw materials to the disposal of materials at the end of life. Aggregated impact on the natural environment at all the stages of the product life cycle is assessed, based on the assumption that processes are interdependent, or that individual manufacturing stages affect one another [22]. LCA ensures a comprehensive overview of the product's environmental impact, taking into account processes that are otherwise excluded, such as extraction of raw materials, transport, etc. [23]. The LCA method is classified as a quantitative tool not only facilitating the classification of certain groups of impact, but also determining the impact quantitatively for each of the measures in use [24]. Owing to the complexity of calculations and sequentiality which can be easily expressed by means of algorithms, the LCA is widely implemented in software tools supporting product environmental assessment [25]. According to ISO 14040:2006, the LCA comprises four stages [26, 27]:

- Goal & scope definition – definition of the product under analysis and its service life, scope of study, data source, target group and intended purpose of the study;
- Inventory analysis – determination of system inputs, outputs and processes, determination of the raw material and energy balance, creation of the product's life cycle;
- Impact assessment – classification of environmental impacts by means of a selected method and determination of their size (categorization and quantitative analysis);
- Interpretation – presentation and critical evaluation of results (this stage is in progress simultaneously with the three other stages).

There are defined methods by which an LCA can be performed, such as e.g. Eco-Indicator 99, IMPACT 2002+ or ReCiPe 2016 Endpoint [28]. In this study, the ReCiPe 2016 Endpoint method, described in detail in the chapter entitled *Methodology of the study*, has been used.

4. SOFTWARE TOOLS SUPPORTING ENVIRONMENTAL ANALYSIS

There is a wide choice of software tools which facilitate the environmental analysis of manufactured products. One group of them are autonomous software tools which require manual and usually time-consuming implementation of the product life cycle. Not integrated into any 3D CAD environment, they do not support any data transfer, such as e.g. product structure. Their ample databases retrieve proprietary data on processes. Typically, the analysis is carried out in accordance with the LCA environmental management technique (discussed in detail in the chapter on LCA) by a method (e.g. Eco-Indicator 99, ReCiPe 2016 Endpoint) implemented into the software. They support extensive analyses of emissions (positive and negative ones), and provide numerical values of emitted substances, gases, etc. Some examples of such software tools are GaBi, SimaPro, Umberto and OpenLCA. SimaPro is one the most commonly used tools. Data on the product can be retrieved from the databases implemented, and the calculation methods correspond to the LCA environmental management technique. Environmental impacts can be imaged for one product assembly, and alternative product assemblies can be compared [29].

Another group are autonomous tools integrated into a 3D CAD environment or one of its modules. Some examples are the Eco Materials Adviser environmental analysis module of Autodesk Inventor and SOLIDWORKS Sustainability of SOLIDWORKS. Solutions of this type streamline work through automated data interchange between a 3D product model and the environmental analysis module, thus saving the designer's time spent on entering the product structure data. Additionally, other data on the manufacturing process can be entered, such as methods of transport, place of production and use, service life, etc., which – as a standard – are not assigned to a 3D model. Analyses performed in such systems are trimmed down to the examination of water and energy consumption, carbon footprint of the manufacturing process, etc. Compared to the analyses performed by the autonomous systems referred to above, these tools are intended for management purposes. They do not support thorough analysis of the environmental impact of designed products throughout the life cycle using the LCA environmental management technique [30].

Many enterprises develop proprietary environmental analysis software for particular products, such as e.g. the Ecodesign Manual by Philips, the Handbook of Volvo, the Environmental Guidelines by Electrolux, etc. [31].

Changes in manufacturing processes aimed at reducing the environmental impact of products throughout the life cycle are driven by the pressure put by industry beneficiaries on environmental protection. Accordingly, the number of software programs supporting environmental analysis, equally customized (adapted for certain products and enterprises), autonomous and integrated into CAD 3D systems, available in the market, is growing rapidly.

A wide spectrum of novel AI-based solutions supporting LCA is described in Section 6.

5. AI-BASED ANALYSIS OF A PRODUCT MANUFACTURED IN AN ADDITIVE TECHNOLOGY

LCA is an environmental tool that typically requires big data to provide indirect measurement of product performance and simulation of proposed scenarios to improve product performance. AI supports LCA on the increasing availability of data and information by combining the concepts of modeling and data analysis, creating LCA based on data mining. The LCA assessment by AI can cover all or only specific steps of the LCA, also as a second opinion system. The typical scientific approach in LCA is based on the life sciences, but this is not always fully possible, also due to the lack of a sufficiently large amount of research. For the above-mentioned reasons, AI-based LCA is now a complementary rather than a base technology.

5.1. Methodology of the study

A comparative AI-based LCA environmental analysis has also been performed for a previously described hand exoskeleton in two alternative versions:

- the base assembly – featuring PLA elements manufactured in an additive technology,

- alternative assembly – featuring ABS elements manufactured in an additive technology.

The study has been conducted in accordance with an original ANN concept taking into consideration LCA four-stage environmental management technique (based on ISO 14040:2006).

5.2. Goal & scope definition

The use of artificial intelligence for LCA assessment allows the existing functionality presented in Section 5 to be extended to include LCA analysis based on data at the two extreme poles of computational analysis complexity:

- incomplete data that does not lend itself to traditional LCA assessment, requiring estimation rather than exact calculation,
- very complex, multidimensional data, from multiple measurements (e.g. from real-time solutions based on the Internet of Things or the Internet of Everything), too complex for traditional calculations and imaging without the use of multidimensional scaling to project a set of parameters into 3D space.

The aforementioned approaches provide an opportunity to take advantage of the fundamental benefits of AI:

- being based on the structures, values, and properties of the data you have, rather than on proven mechanisms and algorithms for analyzing it,
- extraction of rules "on the fly",
- possible lower accuracy (estimation rather than calculation),
- response in all conditions (AI solutions will always give some result, and their operation will not crash, in contrast to a running traditional computer program),
- in some cases: the possibility of learning during operation, adapting solutions better fitted to e.g. specific operating conditions of a device or production line.

For the above reasons, the natural tools used in AI-based LCA analysis will be traditional and deep artificial neural networks (ANN within machine learning (ML) concepts – data driven approach), complemented in some applications by other tool modules such as:

- inference on mobile devices, IoT sensors and effectors for data collection and impact checking/testing,
- decision trees and random forests for working out decision processes,
- fuzzy logic, for analyzing processes describable only linguistically, including ordered fuzzy numbers – for describing and analyzing fuzzy processes where the direction of data change is important (e.g. rapidly rising, slowly falling),
- genetic algorithms for optimization of ANN structures,
- multifractal analysis for the analysis of the degree of data variability, including the analysis of the possibility of trend change on the basis of Hurst index values.

The computerization, automation, and robotization of manufacturing under the Industry 4.0 paradigm will foster the use of AI for LCA analysis through the mass production of sensor and effector data, quality control at every stage of manufacturing, labeling of products and their parts, and the ability to read the aforementioned labels at every stage of a product's life until successful recycling. This will allow LCA simulation effects to be compared with real values, gradually improving the virtual twins of products.

5.3. Inventory (inputs and outputs) analysis

We used a three-tier ANN to estimate the LCA. ANN was built and trained in a MATLAB environment with Neural Networks Toolbox (R2021b version, MathWorks, Natick, MA, USA).

When developing the model, we used:

- data sets from traditional LCA analysis,
- multilayer perceptron (MLP),
- a three-layer neural network of the feed-forward type,
- back propagation error (BP) algorithm, because it is relatively easy to use, fast, simple and easy to program,
- optimization of MLP connection weights based on the minimization of the mean square error function (MSE) between the target and actual results averaged in all teaching examples,
- pre-programming the weights of neural networks to avoid too slow convergence and attractor wedging at local minima instead of searching for a global minimum,
- naive initialization techniques, much simpler than Xavier initialization or ReLu function.

The structure of the ANN used is shown in Figure 1 and Tables 1–3.

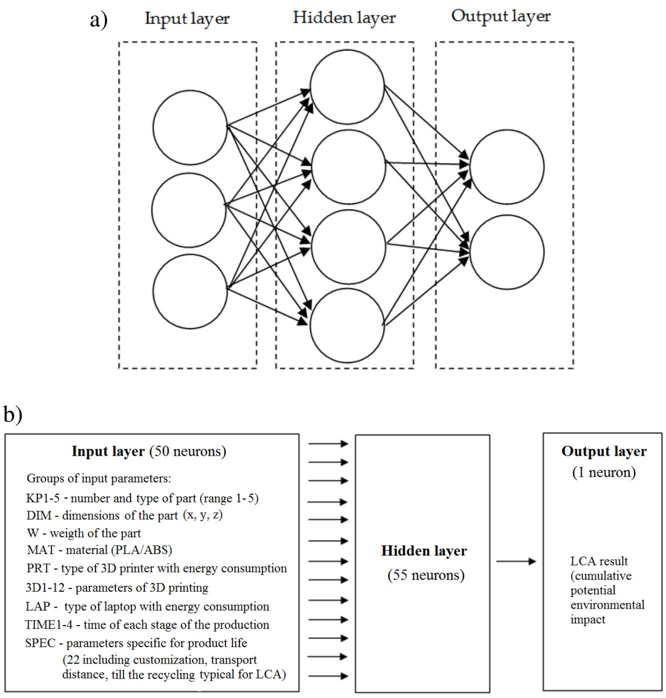


Fig. 1. ANN structure: a) idea, b) realization.

The number of neurons of the input layer is equal to the number of features in the LCA data. The number of neurons of the output layer is equal to the number of outputs associated with the result (here one reflecting the LCA value).

The number of hidden layer neurons, which is responsible for the learning capabilities of the network, is selected experimentally based on the knowledge and experience of the neural network designers and its optimization for a specific angle. In our case, we chose complex optimization criteria, i.e. accuracy and fast convergence of the network to the desired mean square error (MSE) value. Generally, optimizing a neural network might be a complex task.

Each ANN layer contained neurons with the same activation function (Table 1).

Table 1
MLP network model for LCA assessment

NS	AH1	AO
MLP 50-45-1a	Sigmoid	Sigmoid
MLP 50-45-1b	Tanh	Tanh
MLP 50-50-1a	Sigmoid	Sigmoid
MLP 50-50-1b	Tanh	Tanh
MLP 50-55-1a	**Sigmoid**	**Sigmoid**
MLP 50-55-1b	Tanh	Tanh
MLP 50-60-1a	Sigmoid	Sigmoid
MLP 50-60-1b	Tanh	Tanh
MLP 50-65-1a	Sigmoid	Sigmoid
MLP 50-65-1b	Tanh	Tanh

Where: NS – ANN structure; AH – activation function in the hidden layer; AO – activation function in the output layer.

The ANN-based LCA assessment shows that the proposed analysis is fast and accurate for an independently tested product. It is worth noting here that sensitivity of the method was assessed as sufficient, however, further verification in this area is advisable. In subsequent studies, further optimization is necessary, including checking the advisability of using deep learning (DL).

The best results were achieved for the MLP 50-55-1 network with sigmoid activation function (MLP 50-55-1a) (Table 2, Table 3).

Table 2
Selected ANN quality assessment

Network name	Quality (learning)	Quality (testing)
MLP 50-45-1a	0.8778	0.8904
MLP 50-45-1b	0.8801	0.8914
MLP 50-50-1a	0.9017	0.9178
MLP 50-50-1b	0.9023	0.9192
MLP 50-55-1a	**0.9112**	**0.9216**
MLP 50-55-1a	0.9092	0.9177
MLP 50-60-1a	0.9002	0.9134
MLP 50-60-1b	0.8997	0.9102
MLP 50-65-1a	0.8822	0.8956
MLP 50-65-1b	0.8789	0.8912

Table 3
MSE values for MLP neural network

Network name	(R)MSE
MLP 50-45-1a	0.03
MLP 50-45-1b	0.03
MLP 50-50-1a	0.02
MLP 50-50-1b	0.02
MLP 50-55-1a	**0.01**
MLP 50-55-1a	0.02
MLP 50-60-1a	0.02
MLP 50-60-1b	0.02
MLP 50-65-1a	0.03
MLP 50-65-1b	0.03

5.4. Impact assessment

Due to many factors (not only technological, but also environmental or social ones), perhaps in addition to the traditional approach based on life sciences, LCA may need to apply other scientific approaches, including those from social and economic sciences. There is still much work to be done in the methodology for measuring energy and resource consumption for LCAs, hence the need to develop a broad approach to coordinating the various components of different materials and different technologies, needed to produce a finished product (e.g. 3D printed circuit boards). This also applies to the incorporation of elements from natural technologies into the LCA, e.g. wood from forestry as part of the AI-based monitoring of the Earth's natural resources with Overstory. Such real-time insight into the resources of forests and other natural ecosystems of the Earth allows to make faster and more accurate decisions about nature, protecting the Earth's biodiversity, maintaining sustainable development and mitigating climate change on our planet. AI methods in conjunction with LCAs have been applied to agriculture, climate and engineering research (including energy and water efficiency) [32–36], demonstrating high ability to solve complex problems using uncertain, interactive and dynamic characteristics in a cost-effective and efficient manner, improving the quality of your inventory. Its use in industry is only at the beginning.

5.5. Directions for further research

The main problem is the need to learn data sets – we need real life values of LCA to learn the network.

In order to fully identify the AI techniques used in LCA, both new research and literature on the subject is required. AI can be used not only to estimate and calculate the potential effects of change using previously developed models, but also to detect missing data, thus increasing the robustness of the models. In order to increase its reliability, LCA-AI models should be applied on a large scale over a wide range of materials, technologies and industries as well as taught and tested on large sets of various data, and the results should be published in the form of reports [37–42].

6. TRADITIONAL ENVIRONMENTAL ANALYSIS OF A PRODUCT MANUFACTURED IN AN ADDITIVE TECHNOLOGY

6.1. Methodology of the study

A comparative LCA environmental analysis has been performed for a hand exoskeleton in two alternative versions:

- the base assembly – featuring PLA elements manufactured in an additive technology,
- alternative assembly – featuring ABS elements manufactured in an additive technology.

The study has been conducted in accordance with the LCA four-stage environmental management technique (in compliance with ISO 14040:2006).

6.2. Goal & scope definition

A hand exoskeleton developed by scientists of the Kazimierz Wielki University in Bydgoszcz, Poland, has been examined. The study is aimed to determine the environmental impact of the product throughout its life cycle. Two assemblies of the product, with elements made of two different materials (both manufactured in an additive technology), have been examined to find how the change of material affects the software output, i.e. information about the environmental impact of the assembly. The final output is a comparative analysis of the alternative product assemblies, shown as a compilation of graphs generated in the software. The study can support scientists in the selection of material for the exoskeleton.

The product has been assigned a service life of 5 years – at the end of that period, all of its parts should be replaced with new ones.

The scope of the study has been defined as follows: the manufacturing processes of equipment, tools and vehicles used throughout the product's life cycle, such as a truck, a drill-driver, a 3D printer and a laptop, have been excluded from the analysis; however, emissions to the environment in the processes related directly to the manufacturing of the exoskeleton with the use of the above-mentioned equipment, tools and vehicles (e.g. transport of sub-assemblies in the truck) have been included.

The analysis has been performed in the SimaPro software, with data sourced from the literature and software databases. Universal substitutes available in databases have been used in place of the missing data required to create the life cycle of the product (e.g. linear servo controller – electronics, for control units).

6.3. Inventory (inputs & outputs) analysis

At stage one, processes required to develop the product structure, which were missing from the software database, were developed. The focus was put on the additive manufacturing process. All other elements of the two assemblies under analysis were purchased and identical for both assemblies, so they had no impact on the outcome of the comparative analysis. Based on the data sourced from [43], a universal additive manufacturing process was entered for both PLA and ABS, with the respective emissions generated by each material during a one-hour cycle of the 3D printer. Next, the process of additive manufacturing of the assembly parts, namely, finger phalanxes, a metacarpus and a carpal joint (connected by means of supports), a housing for the electronic circuit and fourteen mounting pegs, has been developed. Energy consumption by the 3D printer and the laptop (necessary to adapt a universal exoskeleton design to individual needs of the patient) has also been taken into account. The additive manufacturing process for PLA, implemented into the system, is shown in the screenshot in Fig. 2. The printing process was of the same duration for both assemblies, but energy consumption by the printer was declared higher for ABS than for PLA.

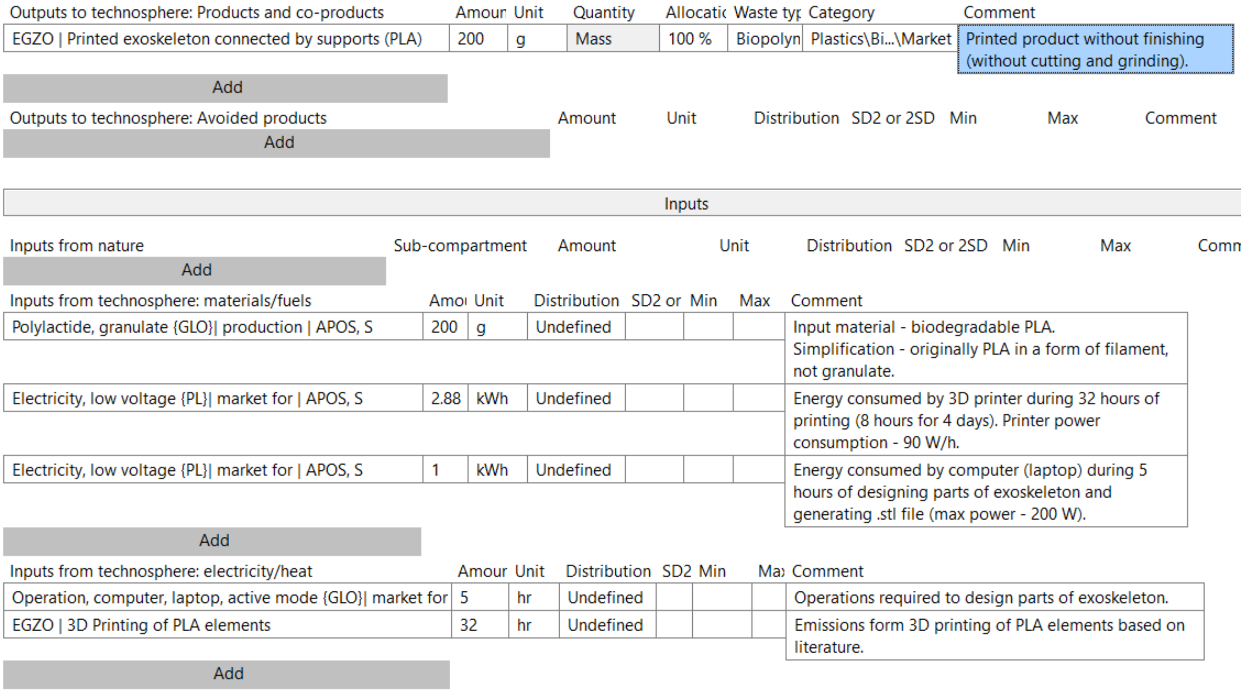
Similarly, the manufacturing process for the polyester elements – a wrist orthosis and a LiIon battery case – was developed. The process was identical for both assemblies. Other subassemblies were simplified (as they did not affect the result of comparative analysis) and based on the data retrieved from the SimaPro database. As mentioned in Section 6.1, substitutes (similar processes for parts manufactured in similar technologies) were used in some assemblies for the data which were missing from the database.

At stage two, the product structure, identical for both assemblies, was developed. Modification of the alternative assembly relative to the base one consisted in using a different material (ABS in place of PLA). The product structure is shown in Fig. 3.

According to Section 6.1, considering the very production of the exoskeleton, the manufacturing processes of equipment, tools and vehicles used in the entire manufacturing process of the product under analysis were excluded from the study scope. However, certain processes related directly to the production of the exoskeleton, in which the above-mentioned equipment, tools and vehicles were used, were identified, namely:

- delivery of the purchased subassemblies and the end product to the customer – transport by a truck (underlying assumption: each subassembly is transported over a distance of 100 km),
- customization of the exoskeleton – performed on a computer in the active mode; duration: 5 hours; mean energy consumption,
- additive manufacturing of exoskeleton elements – with the use of a 3D printer; mean energy consumption,
- assembly of the exoskeleton – energy consumption by a drill-driver for 3 hours of operation.

At the next stage of data preparation for the analysis, information about the service life of the product was entered. The service life was defined as 5 years – after that period all the parts of the product should be replaced with new ones. The process of manufacturing of the carton box in which the end product would be delivered to the end user as well as the transport to the end user by means of a truck were taken into ac-



Outputs to technosphere: Products and co-products	Amour	Unit	Quantity	Allocatic	Waste tyr	Category	Comment
EGZO | Printed exoskeleton connected by supports (PLA)	200	g	Mass	100 %	Biopolyn	Plastics\Bi...\Market	Printed product without finishing (without cutting and grinding).

Add

Outputs to technosphere: Avoided products	Amount	Unit	Distribution	SD2 or 2SD	Min	Max	Comment

Add

Inputs

Inputs from nature	Sub-compartment	Amount	Unit	Distribution	SD2 or 2SD	Min	Max	Comn

Add

Inputs from technosphere: materials/fuels	Amoı	Unit	Distribution	SD2 or	Min	Max	Comment
Polylactide, granulate {GLO}| production | APOS, S	200	g	Undefined				Input material - biodegradable PLA. Simplification - originally PLA in a form of filament, not granulate.
Electricity, low voltage {PL}| market for | APOS, S	2.88	kWh	Undefined				Energy consumed by 3D printer during 32 hours of printing (8 hours for 4 days). Printer power consumption - 90 W/h.
Electricity, low voltage {PL}| market for | APOS, S	1	kWh	Undefined				Energy consumed by computer (laptop) during 5 hours of designing parts of exoskeleton and generating .stl file (max power - 200 W).

Add

Inputs from technosphere: electricity/heat	Amour	Unit	Distribution	SD2	Min	Ma)	Comment
Operation, computer, laptop, active mode {GLO}| market for	5	hr	Undefined				Operations required to design parts of exoskeleton.
EGZO | 3D Printing of PLA elements	32	hr	Undefined				Emissions form 3D printing of PLA elements based on literature.

Add

Fig. 2. Additive manufacturing of elements in PLA

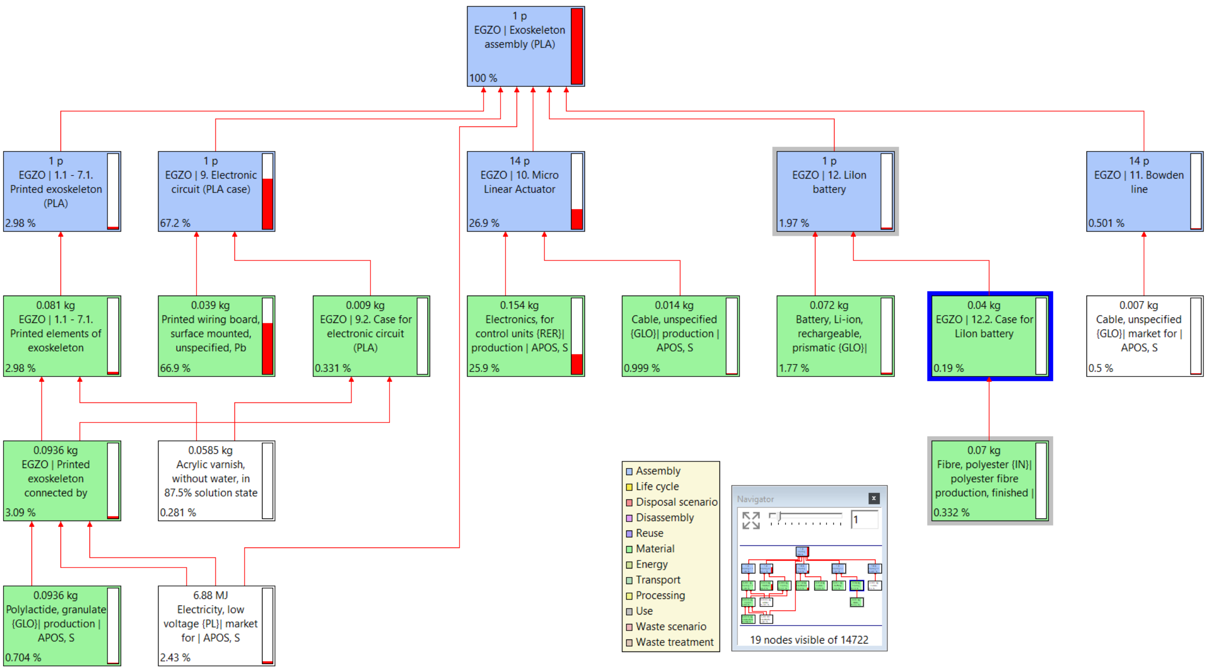


Fig. 3. The most important elements of the product structure

count, and energy consumption during the five years of service life was determined (164.25 kWh, 90 W/day). Consumption of sanitizer was also added for the entire service life (182.5 l, ca. 0.1 l/day). The last stage of the inputs and outputs analysis was the determination of removal from service strategy. Based on the databases available for both alternatives, landfill disposal was selected.

The outcome of this stage was the development of life cycles for the base and alternative assemblies.

6.4. Impact assessment

The analysis was performed by means of the global ReCiPe 2016 Endpoint method (one of the methods implemented in the software, compliant with the LCA environmental management technique). This is one of the most comprehensive methods of assessment, which supports an analysis of cause and effect paths linking midpoint characterization factors with endpoint characterization factors [33, 44]. The assessment relies on 22 indirect impact categories (Fig. 4), which are then assigned to three endpoint area categories (human health, ecosystems, resources) (Fig. 4).

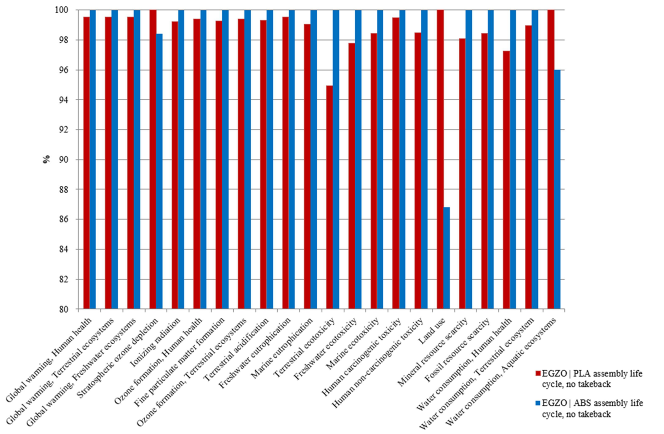


Fig. 4. Results of a comparative analysis of the base assembly (PLA) and the alternative assembly (ABS) – midpoint characterization factors (red bars – PLA assembly life cycle, blue bars – ABS life cycle assembly)

6.5. Interpretation of results

The analysis leads to a direct comparison (visual – on graphs, and quantitative – in tables) of the two versions of the assembly (the base assembly – PLA and the alternative assembly – ABS). As mentioned above, the same purchased subassemblies were used for both assemblies of the product; the only difference between the assemblies was the material used for the parts produced in the additive technology. The differences of the estimated environmental impact (midpoint characterization factors) between the two assemblies throughout their life cycles are shown in the screenshot (Fig. 3).

The base assembly (PLA) is marked in red, the alternative assembly (ABS) – in blue. Values representing the environmental impact of the PLA assembly are higher than those for the ABS assembly only in three of the 22 categories under analysis. Similarly, it follows from an analysis of the endpoint characterization factors – normalization (by the ReCiPe 2016 Endpoint method) – that for each of the categories (human health, ecosystems, resources), values for the life cycle of the ABS assembly are higher than those for the PLA assembly (Fig. 5).

Se	Damage category	Unit	EGZO | PLA assembly life cycle, no takeback	EGZO | ABS assembly life cycle, no takeback
☑	Resources		0.00027	0.000275
☑	Ecosystems		0.0257	0.026
☑	Human health		0.402	0.407

Fig. 5. Comparative analysis results (normalization – ReCiPe 2016Endpoint)

All in all, the alternative assembly has a greater environmental impact than the base one (single score – Fig. 6).

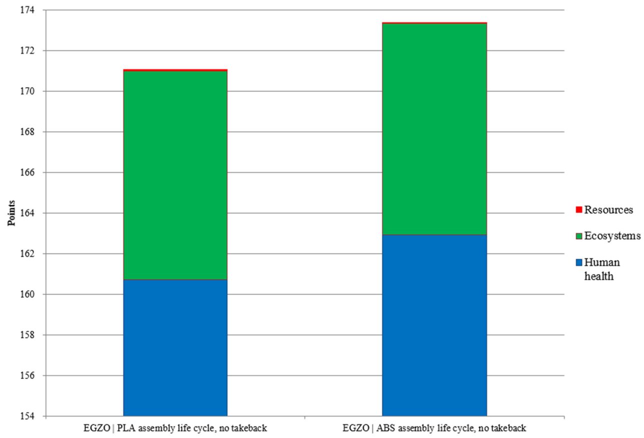


Fig. 6. Comparative analysis results – single score – ReCiPe 2016Endpoint (red – resources, green – ecosystems, blue – humanhealth)

7. DISCUSSION

The SimaPro software used in the study is a tool supporting thorough analysis of the environmental impact of a product throughout its life cycle. The global methods implemented in the software (ReCiPe 2016 Endpoint, Eco-Indicator 99) facilitate calculation of the environmental impact and streamline clear representation of data. To date, we have not observed similar studies in the literature on artificial-intelligent LCA analysis, comparative studies or hybrid solutions combining traditional and AI-based approaches. For the aforementioned reasons, it is difficult for us to make direct comparisons with existing solutions. Nevertheless, this area of research is worth pursuing, and the results obtained and new approaches will be all the more valuable the more complex the planning, design, manufacturing, servicing, after-sales retrofitting and recycling processes. Handling such complex processes as part of the Industrial Internet of Things and Industry 4.0 will require increasingly sophisticated computing tools.

Limitations are posed by databases, which lack some data on particular (often specific) processes necessary to build a precise representation of the product's life cycle. Another difficulty is posed by the fact that manufacturing processes of some subassemblies by third parties are unknown. Meticulous data gathering is required to build a product life cycle in the software which will truly and accurately represent the real life cycle of the product. This applies particularly to their collection in IT databases, which will be the basis for efficient computational analyses using artificial intelligence. It was also shown that metal bases are useful in the production of e.g. dentures. It is easier to optimize them to mimic hard tissues [45].

Further study will focus on minimizing the simplifications made to the product, especially with regard to the disposal of particular assemblies at the end of life. This will allow the concept of computational and hybrid LCA analyses presented in this article to be developed thoughtfully and as quickly as possible. The development of AI-based LCA for small samples is also a challenge.

8. CONCLUSIONS

The results obtained showed that the artificial-intelligent approach can provide an effective way to analyze LCA even in such complex cases as a 3D printed medical exoskeleton. This approach, which is becoming increasingly useful as the complexity of manufactured products increases, will be developed in future studies.

Despite the potential benefits of using AI-based integrated modeling in LCA, the topic is currently not fully explored. AI algorithms in LCA research are applied from the identification of the problem to its solution, therefore the integration between AI and LCA models, also within hybrid solutions, is very important, allowing for the construction of predictive models that increase the effectiveness of decisions being made.

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