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Eco-design for Circularity: Automatic design proposal based on structural and functional definitions of 2nd life components using Generative AI.

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Abstract

Many sustainable design approaches focus on preserving the value of the product when it reaches the end of its life and is assimilated to waste: functional recovery of the product or its modules, material recovery through recycling, or energy recovery. However, to ensure the highest levels of value preservation, another approach is to develop design strategies from end-of-life by reusing all or parts of the products into new ones.

Artificial Intelligence (AI) introduces innovative solutions for circularity and waste management. Currently, design quality heavily relies on human expertise, modeling, and simulation tools. Our research explores the use of AI as an exchange tool between designers and end-of-life stakeholders to understand requirements, search for optimal solutions, and make informed decisions. As such, we aim to develop AI solutions tailored to different stages of the design process within a circular economy framework, focusing specifically on the design of products based on recovered second-life components.

We aim to enhance circularity by using Generative AI for the structural and functional reuse of end-of-life products. For functional reuse, we propose a recommendation system using large language models (LLM), and for structural reuse, we propose creative design ideas using text-to-image models. Advanced technologies like Generative AI are crucial for effective product design and strengthening circular economy implementations.

Keywords: *Circular Design; Circular Economy; Artificial Intelligence; Generative AI; Innovative Solutions*

In recent years, the imperative to address environmental challenges has led to an increased focus on sustainable practices in various industries. One such approach is the development of design strategies *from* end-of- life. This aspect of ecodesign implies considering the reality of the end-of-life treatments of products considered as waste. This enables to promote the functional recovery of all or sub-parts of the whole product (*i.e.*, a module, single component recover, until a structural part), then the material recovery (*i.e.*, recycling) and lastly the energy valorization. Favoring the highest levels of value take back implies proposing new types of uses and design, for repair but also potentially use as primary component/module in product design and manufacturing, different from the original product. We assume that artificial intelligence (AI) technologies in this context will help to introduce innovative solutions for product development or help the optimization of end-of-life product breakdown to get the best component recovery.

This study begins by exploring the use of AI in the context of product design to comprehend the requirements, search for

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solutions that fit with objective performances from the requirements, and make the decisions in this context. Currently, design quality heavily depends on human expertise, coupled with modeling and simulation tools. The objective of this study is to develop specific AI solutions tailored to different stages of the design process within the circular economy framework. Such AI solutions could support designers in developing reuse applications and processes. Specifically, the focus lies on designing products based on recovered second life functional components, exemplifying a design from circularity approach. In this work we focus on complex assembled products coming from manufacturing, ranging from waste electrical and electronic equipment (WEEE) and larger product components such as wind turbine blades.

This paper aims to explore the role of Generative AI in advancing circular design by addressing critical questions about component reuse and sustainability at end-of-life stages. Generative AI refers to a class of AI models capable of autonomously creating diverse digital outputs, such as designs and visual concepts. Common models include large language models (LLMs) for text and generative adversarial networks (GANs) for visual designs, which can be fine-tuned for specific industry needs like circular ecodesign. Specifically, we investigate how AI can propose innovative design modifications that retain structural and functional value, reducing waste and optimizing resource efficiency within a circular economy framework (see *figure 1*). AI-driven eco-design aims to help several types of expertise within the circular economy framework, and to ease exchange between these different actors:

Designers are creating adaptable designs for second-life applications. They need to have information on the second life modules/ components/ material: their performances, remaining functionalities/ reliability and the number of available elements. They search for applications where these components could be reused.

Circular Engineers are developing efficient component recovery from end-of-life process. They do have identification, sorting and characterization activities. They need to evaluate the remaining functional interest of components / structural parts. They must provide a reliability quotation, event certification, for second used components.

Recyclers are material oriented, seeking to valorize materials by liberating and concentrating them from mixed batches. Over-sorting strategy can allow to get the high value shredded grade material needed for critical material recovering.

This paper focuses on the use of Generative AI to answer the question: How to increase design from circularity.

- Section 1 introduce the state of the art on this topic;
- Section 2 discuss AI-generated content in Design;
- Section 3 explains the development of large language models in Eco-Design based on an electric motor case study;
- Section 4 presents a text-to-Image models in Eco-Design of 2nd life of a wind turbine blade;
- Section 5 will conclude on the work done.

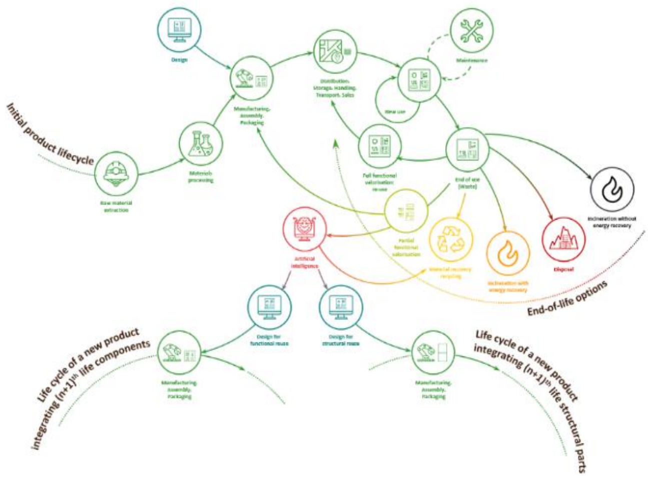

Figure 1. Integration of AI in a product's life cycle to extend its lifespan.

1. Literature Review

An automatic waste segregation system can be a viable solution to improve the circularity and to boost up the circular economy. Previous works could efficiently propose AI tools to segregate waste into the different parts using classification and object detection algorithms [1], [2]. Using AI tools can help preserving not only materials, but also parts and functional sub-assemblies by reintegrating them into new products. Hence, the process helps to satisfying the principles of the circular economy by limiting the extraction of primary resources.

Some previous work has used AI in creative product design to boost business success. Quan *et al.* used the convolutional neural network-based neural style transfer to reconstruct and merge color and pattern features of the style image, which are then migrated to the target product [3]. The generated new product image could not only preserve the shape of the target product but also have the features of the style image. Therefore, the new product design could better meet the needs of the users and implementation of this proposed method was demonstrated in detail through a case study of female coat design. In another example, Zhu *et al.* used machine learning and computer vision technologies to automatically design new "must-have" fashion products with popular styles discovered from fashion product images and historical transaction data. The result shows that their method could successfully generate combinations of interpretable elements from different popular fashion products [4].

In the field of car design, Radhakrishnan *et al.* proposed to implement a system based on generative adversarial networks (GANs), to create novel car designs from a minimal design studio sketch. This is achieved by learning to interpret a preliminary sketch drawn by a designer, to generate novel visual designs in a matter of seconds, which may otherwise require considerable time and effort. While the system enhances the productivity of the designer, the machine learning enhanced design visualizations can cut costs during the product prototyping stage [5].

One of the interesting subjects is how to deploy AI models in design platforms to make automatic decision for different stages of design. Pinquié *et al.* could previously use natural language processing (NLP) techniques to automatically generate parametric property-based requirements from unstructured and semi-structured specifications [6]. They could illustrate their approach through the design of a mechanical ring by deploying NLP model in ENOVIA/CATIA V6 software solution of Dassault Systèmes.

Lastly, McKay *et al.* also showed an interest to integrate machine learning technologies into design workflows with a view to improving the performance of the product development process. They applied machine learning to two shape-based design challenges: clustering visually similar shapes and shapes that are likely to be manufactured using the same primary process. They reported early results and concluded with issues for design descriptions that need to be addressed if the full potential of machine learning is to be realized in engineering design [7].

2. AI-Generated Content in Product Design

AI-generated content (AIGC) refers to content created autonomously by artificial intelligence models.

AIGC can produce a wide variety of digital outputs, such as text, images, videos, music, and even complex designs, without the need for intensive human intervention. With the fast advancement of machine learning, particularly in generative models like generative pre-trained transformers (GPTs) for text and GANs for visuals, AIGC has the potential to revolutionize numerous fields, including product design. This study explores how AIGC influences product design and helps companies innovate faster, more efficiently, and more sustainably.

Generative AI models are trained on vast datasets containing numerous design possibilities, trends, and user preferences. By leveraging this data, AIGC can produce multiple iterations of design concepts that meet predefined criteria, such as aesthetic appeal, functional performance, or sustainability. These AI models also allow for optimization based on real-time feedback, making product design more adaptive and efficient.

2.1. Automated Design Generation

One of the most transformative aspects of AIGC in product design is the ability to autonomously generate design concepts. Designers can input specific parameters, such as material constraints, cost limitations, or ergonomic considerations, and let AI generate multiple design options. This technique, often referred to as generative design, is already being employed in industries like automotive and aerospace. For example, General Motors used generative design software to create a lightweight seat bracket [8]. AI generated more than 150 design options, optimizing for strength, material use, and manufacturability. The final result was a 40% lighter part, made from a single piece of material, which contributed to better fuel efficiency. In other study [9], a first group of designers had to create a massage office chair in a traditional collaborative manner and a second one had to create a hamburger vending machine using Midjourney AIGC tool. After the quality of both designs had been assessed by external designers, first group received scores of 78 and 80 out of 100, while second one received scores of 85 and 88 out of 100, showcasing the positive impact of AIGC on design quality.

2.2. Sustainability and Eco-Design

Generative AI can play a significant role in ecodesign, focusing on minimizing environmental impact through the choice of sustainable materials, energy-efficient designs, and waste reduction. AI can predict the environmental impact of different materials and suggest sustainable alternatives. It can also optimize designs to use fewer resources while maintaining functionality and durability. For instance, Autodesk's generative design tools are commonly used to create more sustainable products. These AI systems generate designs that optimize material usage and reduce waste during manufacturing, contributing to the circular economy.

2.3. Customization and Personalization

AIGC enables product designs to be tailored to individual users' needs through mass customization. AI can analyze user preferences, bio-metric data, or feedback to automatically generate personalized products, ranging from fashion items to consumer electronics. For example, companies like Nike are using AI to offer customizable shoe designs that reflect a user's style and performance needs. In addition, 3D printing combined with AI-generated designs has opened new possibilities for creating personalized medical devices like prosthetics and orthotics, which are customized to a user's specific body shape and size.

2.4. AI-Assisted Visualization

AIGC can enhance the visualization process in product design by generating highly accurate and detailed 3D models, simulations, and renderings. For example, text-to-image models like DALL-E [10] can create visual concept art based on written descriptions, which is valuable during the initial brainstorming and conceptual stages. This allows designers to quickly experiment with multiple ideas, without needing to manually draft each one.

2.5. Rapid Prototyping

AIGC supports rapid prototyping by automatically generating digital 3D models that can be directly manufactured through technologies like 3D printing or CNC machining. This accelerates the iterative process of testing and refining designs. AI can also analyze feedback from each prototype to adjust the design, improving efficiency and reducing costs associated with traditional prototyping methods.

2.6. Collaboration Between AI and Human Designers

A key advantage of AIGC is its ability to enhance collaboration between AI and human designers. AI can generate a wide variety of ideas or solutions that designers might not have considered, allowing them to focus more on decision-making and creativity. For example, AI might suggest innovative shapes or configurations that meet the technical specifications, while designers refine these options for aesthetics and usability.

AIGC is set to revolutionize product design by enhancing creativity, speeding up the design process, and making eco-friendly choices more accessible. Through the use of AI in areas like generative design, sustainability, personalization, and rapid prototyping, companies can create more innovative products that meet consumer needs while minimizing environmental impact. As AI technologies continue to advance, AIGC will likely become an even more integral part of the design landscape, offering new possibilities for what can be created and how it is brought to market.

3. Large Language Models in Eco-Design

With increasing pressure to reduce environmental impacts and promote sustainability, industries are embracing ecodesign strategies, which focus on minimizing waste and optimizing the lifecycle of products. Electric motors, which are widely used in industries ranging from manufacturing to transportation, present an excellent opportunity for advancing ecodesign practices. The reuse of motor components after disassembly can reduce material waste, energy consumption, and environmental degradation.

Previously it has been described how modularity can be used to meet the demands of circularity in the design of electric motors by considering various factors such as disassembly, repair and maintenance, reuse, upgrade, and recycling. [11]

In this study we propose the development of a chatbot powered by large language models (LLMs) and fine-tuned on data extracted from electric motor catalogues, specifically from the Menzel Motors database [12]. The chatbot will serve as an ecodesign assistant, providing recommendations for reusing electric motor components after disassembly. Using the Mistral 7B model [13] for fine-tuning, the chatbot will help engineers and designers identify creative and sustainable applications for motor components, thereby enhancing the ecodesign process (see *figure 2*).

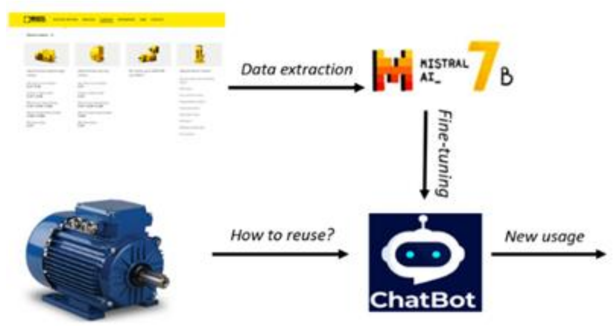

Figure 2. LLM chat-bot for end-of-life electric motors.

Electric motors contain valuable materials such as metals, plastics, and electronics that can be reused in various applications. After such a motor reaches its end of life, many of its components (e.g., stators, rotors, bearings, or casings) can be repurposed in other industrial equipment, new motors, or even completely different products.

However, understanding how to efficiently reuse these components can be complex. This is where the power of LLMs and chat-bots comes into play. By analysing detailed information from electric motor catalogs, the chat-bot can provide intelligent recommendations for re-purposing these components, leading to more sustainable product life cycles.

The key components of the chat-bot development process include:

1. Data Extraction
The process begins by extracting data from PDF catalogues provided by Menzel Motors. These catalogues contain detailed specifications about various motor components, their constituents, and their applications. Using NLP techniques, this data can be parsed into a structured format.

2. Fine-Tuning the LLM
The extracted data can be used to fine-tune the Mistral 7B model. Fine-tuning allows the model to specialize in understanding the technical and contextual information associated with electric motors and their components. This enables the chatbot to provide precise recommendations for component reuse based on specific characteristics such as material type, dimensions, and energy requirements.

3. Chatbot Development
The chatbot can be developed to interface with users, typically engineers and product designers. Users can query the chatbot about potential reuse cases for disassembled components. For example, a designer might ask, “How can I reuse the rotor from a 100-kW induction motor?” The chatbot would then analyse the component's specifications and provide a list of potential applications, considering ecodesign principles such as energy efficiency, material conservation, and waste minimization.

4. Recommendation Engine
The recommendation engine is the core functionality of the chatbot. It is powered by the LLM, which evaluates the extracted data and suggests ways to reuse or recycle motor components. The recommendations could range from direct reuse in new motors to innovative applications in different industries. For instance, motor shafts could be repurposed in mechanical systems, or the copper windings could be recycled for use in electrical applications.

The ecodesign potential of this chatbot lies in its ability to identify sustainable pathways for motor components. Here are some practical examples of how components can be reused:

- **Stators and Rotors** can be reused in refurbished or newly manufactured electric motors. The chat-bot could suggest modifications to the stator or rotor that would allow them to be fitted into new motors with different specifications.
- **Bearings** can be repurposed in mechanical systems such as conveyor belts or other rotating equipment. The chat-bot might recommend applications based on the wear and condition of the bearings.
- **Casings** of motors can be recycled into raw material for construction or repurposed for housing other mechanical or electrical components. The chat-bot could suggest sustainable practices for either recycling or repurposing.

• **Copper Windings** can be extracted and reused in various electrical applications, such as new motors, transformers, or power cables. The chat-bot can analyze the condition of the winding and recommend how best to reuse the copper in new products.

The development of a chat-bot powered by large language models and fine-tuned on electric motor data offers a promising approach to enhancing ecodesign in the industry. By analyzing the potential for component reuse after disassembly, this AI-driven system can provide valuable recommendations that reduce waste, conserve resources, and contribute to more sustainable product life cycles. The application of LLM chatbots to electric motor reuse presents a novel opportunity. As industries continue to prioritize sustainability, the role of AI in ecodesign will only become more critical.

4. Text-to-Image models in Eco-Design

Wind turbine blades contain fiber reinforced polymers which make them a challenge when reaching their end of life. Joustra et al. previously investigated their structural reuse, and they developed a new segmentation approach which was applied to a reference blade model [14][15]. However, thus far, structural reuse of wind turbine blades mostly resulted in occasional architectural object or outdoor furniture. As the volume of end of life wind turbine blades keep increasing, scalable solutions for reusing these high-end materials are needed. To develop creative and feasible design ideas using end of life wind turbine blades, a wind turbine blade case study will be performed in collaboration with TU Delft.

Text-to-image models, such as Midjourney, have shown significant potential to propose feasible and creative design ideas in various domains, including product design. When applied to the new design ideas (outdoor furniture, bridge, bikes storage, children playground, etc.) using end-of-life wind turbine blades, these AI-generated models can support circular design strategies by generating innovative and sustainable design alternatives. In this context, AIGC tools can help designers explore new shapes, structures, materials, and functionalities for wind blades that align with circular economy principles.

One of the primary advantages of using text-to-image models in wind blade turbine design is their ability to quickly generate numerous creative design proposals. These AI models can take textual inputs describing key design constraints such as environmental sustainability, material reuse, energy efficiency, and aerodynamic performance and transform them into detailed visual concepts. These concepts can then be refined further through iterative collaboration between designers and AI models.

To achieve a comprehensive and innovative wind blade turbine design, models such as DALL-E, Stable Diffusion [16], or Midjourney can be utilized. DALL-E and Stable Diffusion offer more open flexibility for custom fine-tuning with specific datasets, allowing them to adapt to niche domains like wind blade turbine design. On the other hand, Midjourney is more generalist and does not offer the same customization. This makes fine-tuning models like DALL-E or Stable Diffusion preferable when seeking highly specialized solutions.

Fine-tuning a text-to-image model is a key step to ensure the AI understands and generates relevant solutions aligned with the wind blade turbine circular design context. Instead of relying on a generic tool like Midjourney, fine-tuning allows for better customization and control over the outputs (see *figure 3*). This method is especially useful for industrial applications where domain-specific expertise and functional constraints are critical to producing designs that are both feasible and innovative.

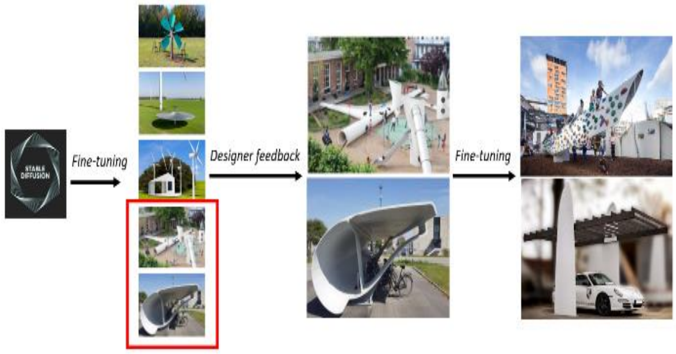

Figure 3. Envisioned workflow for AI-supported, Text-to-image concept development for ecodesign from end-of-life wind turbine blades.

1. Data Collection

The first step is to collect a diverse dataset of images and design references related to wind blade turbines, particularly focusing on circular design strategies. The dataset should include images of wind turbines, blade materials, manufacturing processes, disassembly methods, and examples of reuse or recycling. Additionally, the dataset should include images of aerodynamics and environmental considerations to ensure that the model is equipped to generate relevant design outputs.

2. Fine-Tuning the Model

Fine-tuning a model like DALL-E or Stable Diffusion involves training the AI on the specific dataset of wind blade turbine designs. This process allows the model to become familiar with the specific features, structural requirements, and design variations related to circular economy principles. By adjusting the weights of the neural network, the model will be able to generate more accurate and domain-specific images that cater to the wind blade design.

3. Generating Initial Design Proposals

Once the model has been fine-tuned, designers can begin generating initial design proposals. By inputting specific text prompts that include design requirements, such as "repurposing of wind turbine blade as outdoor furniture" or "a house made out of wind turbine blades", the model will generate images that reflect these ideas. In practice, designers should generate approximately 20 to 30 different design proposals in the initial round. These design proposals will vary in terms of form, material use, and feasibility, allowing for a broad exploration of potential design directions.

4. Iterative Refinement

After the first round of image generation, the designers will assess the initial outputs and provide feedback for refinement. This step allows for iterative improvement, where the model can be retrained or adjusted based on specific feedback, such as improving the design's structural integrity or optimizing the material choices for sustainability. This would involve 2-3 rounds of refinement, where the number of generated designs narrows down to 5-10 high-potential solutions.

5. Collaboration and Finalization

Once a set of promising wind blade turbine designs has been generated, interdisciplinary collaboration between designers, engineers, and material scientists can help refine the most promising concepts. The AI-generated designs will be used as a base for further refinement and final adjustments, incorporating real-world engineering constraints, material choices, and performance simulations.

The application of text-to-image models in the wind blade turbine design process presents a promising avenue for advancing circular design strategies. By fine-tuning models like DALL-E or Stable Diffusion, designers can harness AI to generate creative, feasible, and sustainable design proposals.

5. Conclusions

When the product reaches its end of life, conventional treatment options are available. It can be entirely reused, otherwise it goes through the dismantling process. Its functional sub-assemblies can be reintegrated into the same product. AI can help to identify reuse options into new products, thus preserving their functional or structural value.

Generative AI models, including LLMs and text-to-image models, hold immense potential to enhance ecodesign and advance circular strategies across industries. These AI-driven systems excel in analyzing vast amounts of data and generating innovative solutions, offering a unique advantage in designing products with sustainability in mind. LLMs can be fine-tuned on domain-specific information, such as electric motor data, to intelligently assess component reuse after disassembly.

Similarly, text-to-image models, such as DALL-E or Stable Diffusion, can assist in the creative design process by generating visually compelling, technically sound design proposals. When applied to circular design strategies, such as wind turbine blade development, these models can accelerate the creation of sustainable solutions that prioritize resource efficiency and recyclability.

AI-powered tools can provide intelligent recommendations, promoting resource efficiency, and inspiring novel design approaches. However, such tools need to be validated. Therefore, we propose a validation methodology which includes cross-verification by domain experts (designers, engineers, recyclers), iterative feedback cycles, and simulation testing to confirm that AI-generated design recommendations meet industry standards and sustainability goals.

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References

[1] M. S. Nafiz, S. S. Das, M. K. Morol, A. A. Juabir, et D. Nandi, «ConvoWaste: An Automatic Waste Segregation Machine Using Deep Learning », arXiv, arXiv:2302.02976, févr. 2023. doi:10.48550/arXiv.2302.02976.

[2] K. Lin et al., « Deep convolutional neural networks for construction and demolition waste classification: VGGNet structures, cyclical learning rate, and knowledge transfer », J. Environ. Manage., vol. 318, p. 115501, sept. 2022, doi: 10.1016/j.jenvman.2022.115501.

[3] H. Quan, S. Li, et J. Hu, « Product Innovation Design Based on Deep Learning and Kansei Engineering », Appl. Sci., vol. 8, no 12, Art. no 12, déc. 2018, doi: 10.3390/app8122397.

[4] J. Zhu, Y. Yang, J. Cao, et E. C. F. Mei, « New product design with popular fashion style discovery using machine learning », Springer, 2018. doi: 10.1007/978-3-319-99695-0_15.

[5] S. Radhakrishnan, V. Bharadwaj, V. Manjunath, et R. Srinath, « Creative Intelligence Automating Car Design Studio with Generative Adversarial Networks (GAN) », in Machine Learning and Knowledge Extraction, A. Holzinger, P. Kieseberg, A. M. Tjoa, et E. Weippl, Éd., in Lecture Notes in Computer Science. Cham: Springer International Publishing, 2018, p. 160 175. doi: 10.1007/978-3-319-99740-7_11.

[6] R. Pinquié, P. Véron, F. Segonds, et N. Croué, « Natural Language Processing of Requirements for Model-Based Product Design with ENOVIA/CATIA V6 », in Product Lifecycle Management in the Era of Internet of Things, vol. 467, A. Bouras, B. Eynard, S. Foufou, et K.-D. Thoben, Éd., in IFIP Advances in Information and Communication Technology, vol. 467. , Cham: Springer International Publishing, 2016, p. 205 215. doi: 10.1007/978-3-319-33111-9_19.

[7] A. McKay, T. A. Hazlehurst, A. de Pennington, et D. C. Hogg, « Design descriptions in the development of machine learning based design tools », Proc. Des. Soc., vol. 3, p. 1227 1236, juill. 2023, doi: 10.1017/pds.2023.123.

[8] Driving a lighter, more efficient future of automotive part design. https://www.autodesk.com/customer-stories/general-motors-generative-design

[9] Hu Yin, Zipeng Zhang, Yuanyuan Liu. The Exploration of Integrating the Midjourney Artificial Intelligence Generated Content Tool into Design Systems to Direct Designers towards Future-Oriented Innovation. December 2023, Systems 11(12):566. doi: 10.3390/systems11120566

[10] Aditya Ramesh, Mikhail Pavlov, Gabriel Goh, Scott Gray, Chelsea Voss, Alec Radford, Mark Chen, Ilya Sutskever. Zero-Shot Text-to-Image Generation. February 2021. DOI: 10.48550/arXiv.2102.12092

[11] T. T. Romano, T. Alix, Y. Lembeye, N. Perry, et J.-C. Crebier, «Towards circular power electronics in the perspective of modularity », Procedia CIRP, vol. 116, p. 588 593, janv. 2023, doi: 10.1016/j.procir.2023.02.099.

[12] Menzel Motors catalogues. https://www.menzel-motors.com/catalogue/

[13] Albert Q. Jiang, et all, "Mistral 7B", doi:10.48550/arXiv.2310.06825

[14] J. Joustra, B. Flipsen, et R. Balkenende, « Structural reuse of high-end composite products: A design case study on wind turbine blades », Resour. Conserv. Recycl., vol. 167, p. 105393, avr. 2021, doi: 10.1016/j.resconrec.2020.105393.

[15] J. Joustra, B. Flipsen, et R. Balkenende, « Structural reuse of wind turbine blades through segmentation », Compos. Part C Open Access, vol. 5, p. 100137, juill. 2021, doi: 10.1016/j.jcomc.2021.100137.

[16] Jonathan Ho, Ajay Jain, Pieter Abbeel. Denoising Diffusion Probabilistic Models. Dec 2020. DOI: 10.48550/arXiv.2006.11239.