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Towards proactive design for sustainability in industry 4.0/5.0

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ABSTRACT: The paper proposes an approach called proactive design for sustainability (DfS) in the context of Industry 5.0, for human-centred innovation and environmental sustainability, combined with the technological focus of Industry 4.0. Computer Aided Design (CAD) must integrate sustainability considerations into product development, with the use of Artificial Intelligence (AI), Digital Twins (DTw) and the Internet of Things (IoT) to dynamically monitor and optimise environmental impacts during the design process, with the integration of Key Sustainability Indicators (KSI) into the CAD interface to enable informed decision-making, aligning design parameters with resource availability and environmental constraints. A case study of an autonomous mobile robot (AMR) will show how operational data from the product lifecycle, combined with AI predictions, can reduce energy consumption and emissions.

KEYWORDS: ecodesign, digital twin, industry 4.0, artificial intelligence, computer aided design (CAD)

1. Introduction and context

Design for Sustainability (DfS) responds to environmental challenges by articulating technological advances from Industry 4.0 with the human and sustainable approaches promoted by Industry 5.0 (Vilochani et al., 2024). However, most of the ecodesign approaches still rely on iterative assessments where environmental impacts are evaluated after key design decisions have already been made (Rossi et al., 2016), requiring subsequent adjustments in later phases of the product life cycle (Pigosso et al., 2015; Pigosso and McAloone, 2016). The proposal fills this gap by directly integrating sustainability indicators powered by internet of things (IoT) data, predictive models based on digital twins (DTw) and artificial intelligence (AI) into computer-aided design (CAD) tools. Thus, designers' decisions adjust in real time to environmental constraints, improving flexibility and responsiveness (Maccioni and Borgianni, 2019). The methodology is structured around four key sustainability indicators (KSIs) aligned with sustainable development goals[1] (SDG) indicators (Lacasa et al., 2016). Capitalizing on existing DfS frameworks (Rio et al., 2013; Villers et al., 2024) and proactive design concepts (Demoly et al., 2013), this approach directly integrates environmental analyses into CAD environments. Two main questions structure this research: (RQ1) How to effectively exploit field data and AI to integrate sustainability from the early design stages? (RQ2) How to reconcile ecological constraints and performance requirements? The article reviews the state of the art (section 2), the methodological principles (section 3), the use case on an autonomous robot mobile (AMR) (section 4), the challenges encountered (section 5), then concludes on the perspectives opened (section 6).

[1] https://unstats.un.org/sdgs/metadata/

2. Literature review

2.1. Principles of proactive design for sustainability in Industry 4.0/5.0

Industry 5.0 represents an evolution of 4.0 a move towards intelligent systems that work closely with designers to drive sustainable innovation (Lu et al., 2022). Proactive design goes beyond ecodesign in its ability to anticipate and integrate sustainability constraints from the earliest design phases, enabling real-time impact assessment and adaptive decision-making (Pigosso and McAloone, 2016). Rather than adjusting environmental impact after the fact, proactive design applies sustainability criteria from materials selection through to end-of-life (Demoly et al., 2013; Marconnet et al., 2024b). This approach is based on four fundamental principles: environmental anticipation, dynamic life cycle monitoring, AI-based decision support and interdisciplinary collaboration (Rossi et al., 2016, 2019; McAloone and Pigosso, 2018). Maud Rio et al. (2013) highlights the importance of interoperability between designers and environmental engineers to improve eco-efficient practices (Rio et al., 2011, 2013). The proposed methodology uses advanced tools such as IoT and DTw for resource monitoring and life cycle impact simulations (He et al., 2018; Mouflih et al., 2023). DTw are now an interesting avenue for recovering data directly from the field. This data provides design teams with better visibility on the evolution of the product during its life cycle, as well as its potential environmental consequences (Klewitz and Hansen, 2014). By combining them with decision-making tools using artificial intelligence, it becomes possible to assess, or even anticipate, these impacts from the very first technical choices phases (Ahmadi et al., 2016). In addition, the approach is in line with the logic of the circular economy, thus favoring rational management of resources and waste reduction, with the ecological and economic priorities of Industry 5.0 (Geissdoerfer et al., 2020; Ivanov, 2023).

2.2. Key sustainability indicators (KSIs) in proactive design for sustainability with CAD tools

Key sustainability indicators (KSIs) are quantitative measures that allow the real-time assessment of the environmental, economic and social impacts of a product (Lacasa et al., 2016; Marconnet et al., 2024a). The approach is mainly based on four KSIs, specifically chosen to meet the objectives of SDG 12 - Responsible Consumption and Production[2]: (1) energy efficiency, assessed by the energy consumption required for each functional unit produced (Hoang et al., 2017); (2) material efficiency, estimated by the proportion of materials actually transformed compared to the initial raw materials (Henriques and Catarino, 2015); (3) product/component efficiency, which aims to improve lifespan, ease of maintenance and rational resource management (Maxime et al., 2006); and finally, (4) system efficiency, i.e. the overall capacity to efficiently coordinate all subsystems (Chamchine et al., 2006). These indicators are integrated directly into the interfaces of CAD tools to provide designers with immediate feedback on the ecological consequences of their choices (Gaha et al., 2013; Goldrath et al., 2015). For example, CAD interfaces instantly display data such as the energy consumed per task or the rate of recycled materials. These indicators, fed by operational data collected on products and within connected workshops, allow immediate reactivity to environmental constraints (He et al., 2018). This rapid adjustment capacity appears essential, particularly in the face of increasingly limited resources and new ecological constraints. Indeed, Industry 5.0 specifically encourages the development of systems capable of instantly adapting to environmental changes thanks to IoT sensor networks, digital twins and AI predictive models (Mele and Russo-Spena, 2015).

3. Proposal of a proactive design for sustainability framework

The methodology (Figure 1) leverages IoT data to feed KSI into DTw streaming embedded in CAD. Using AI, it enables immediate visualization of environmental impacts, adjusting engineering decisions in real time based on precise sustainability targets, at the component and overall system levels. The method is based on a bottom-up approach, from data collection to design improvement, with iterative adjustments ensuring compliance with environmental constraints and optimization of energy consumption.

[2] https://www.globalgoals.org/goals/12-responsible-consumption-and-production/

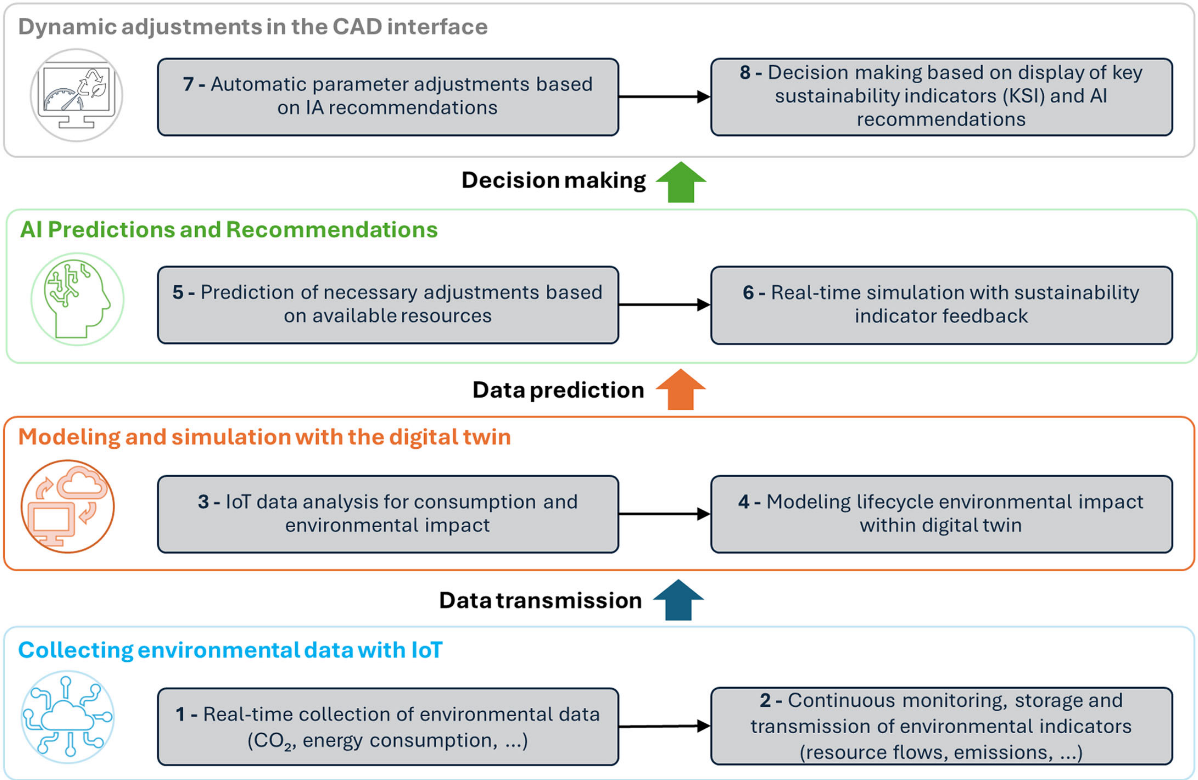

Figure 1. Proactive design for sustainability framework

The process is as follows:

1. ***Step 1 - Real-time collection:*** IoT sensors measure critical environmental indicators such as energy consumption, CO_2 emissions, and resource flows. The data is collected in real-time within the operational context, such as data from a connected system (machine tools, AMR, cobot, etc.) in a smart factory. To guarantee reliability, IoT data is filtered using predefined criteria such as update frequency, contextual relevance and consistency with historical data sets stored in product lifecycle management (PLM) databases, such as enterprise resource planning (ERP), or life cycle assessment (LCA) (Barrios et al., 2022). Another example would be the real-time energy consumption of the product to compare the availability of energy resources, to know the use of renewable energies to minimize dependence on fossil fuels. Additionally, planetary resource limits, such as carbon emissions or freshwater availability, can be shared into databases (e.g. ecoinvent). Data sources include established databases for life-cycle impact assessments, providing information for emissions, energy use and material sustainability. Data sources for these limits include reliable sources of such data include the IPCC (Intergovernmental Panel on Climate Change) for carbon emission thresholds and global climate models [3], the Global Footprint Network, indicators such as Earth Overshoot Day [4], the World Resources Institute for global freshwater scarcity and land-use pressures [5], and the International Energy Agency (IEA) for energy resource availability and fossil fuel dependency limits [6].
2. ***Step 2 - Continuous monitoring, storage and transmission:*** The collected data is continuously transmitted to centralized databases or directly to a DTw for processing. The data serves as a basis for analysis and simulation. Assuming that the relevant data has already been identified, the process focuses on continuous monitoring and storage of key indicators for real-time use in the

[3] https://www.ipcc.ch/
[4] https://www.footprintnetwork.org/
[5] https://www.wri.org/
[6] https://www.iea.org/

DTw. Integrating this data directly into the company's existing information systems (e.g. LCA databases, ERP, product data management (PDM) systems or manufacturing execution systems (MES)) provides a detailed and realistic view of the environmental impacts related to raw materials, actual energy consumption and possible operational losses. This approach thus reduces the gap often observed between theoretical estimates and reality on the ground.

3. ***Step 3 - IoT data analysis:*** Once collected, the raw data is analyzed to identify trends in resource consumption or environmental impacts. This can reveal specific energy losses, for example, related to specific tasks. Examples include analyzing the energy impact of AMR wheel friction or battery charge cycles.
4. ***Step 4 - Modeling lifecycle environmental impact within digital twin:*** The DTw may allow the modelling of environmental impacts over one or more product life cycles, such as assembly, use, disassembly, ... Simulation is essential for comparing multiple design options. For example, it can simulate the use of recycled materials (recycled composites versus aluminum with a specific weight) to reduce overall energy consumption. The phase uses LCA databases or knowledge-based engineering (KBE) in PLM systems to quantify impacts.
5. ***Step 5 - Predictions of necessary improvment:*** AI algorithms leverage simulation results and available environmental data to recommend design improvments or operational changes. AI can suggest geometry improvements to maximize the use of renewable energies during peak hours.
6. ***Step 6 - Real-time simulation with sustainability indicator feedback:*** Designers visualize simulation results and AI predictions in real time, showing the environmental implications of each possible improvement. For example, a heat map can show high-density tasks of energy consumption via updated KSIs, such as energy efficiency and CO_2 emissions per task.
7. ***Step 7 - Automatic parameter adjustments:*** AI recommendations are directly applied in the CAD system. The technical parameters of the products are automatically adjusted to achieve the defined sustainability objectives. For example, this may involve modifying certain geometries to reduce the amount of material used or adapting the product to local energy specificities.
8. ***Step 8 - Decision making based on sustainability indicators:*** At this stage, the designers' technical choices are directly based on the Key Sustainability Indicators (KSIs), particularly focusing on the use of renewable energy and the reduction of CO_2 emissions. These essential indicators (energy efficiency in kWh per task, material efficiency and CO_2 emissions) are displayed in real time in the CAD interface, in line with the thresholds recommended by the IPCC. Designers optimize parameters such as material selection or operational planning rather than major geometric changes. KSIs are essential for real-time decision-making and are evaluated via a multi-criteria decision matrix (Table 1), aligning design with sustainability goals (Janeiro and Patel, 2015; Diaz-Balteiro et al., 2017). The four KSI selected to meet SDG 12 (energy efficiency, material efficiency, product/component efficiency and system efficiency) are adaptable according to the specificities of industrial contexts. An overall score is assigned to each indicator to identify those that require direct dynamic monitoring within the CAD. This assessment is based on several weighted criteria: relevance (R), measurability (M), comparability (C), influence (I), integration (In), communication (Com) and legitimacy (L). The weighted formula (Equation 1) thus makes it possible to determine precisely which KSIs to integrate as a priority to best guide designers' choices towards a truly sustainable approach.

$$KSI\_Score_j = \sum_{i=1}^{7} w_i \cdot S_{ij} \tag{1}$$

Where:

- w_i: Weight assigned to criterion (e.g., relevance, measurability). In this case, all criteria have the same weighting (w_i). However, weightings can be adjusted to reflect specific industrial contexts in which certain criteria, such as relevance or influence, take priority.
- S_{ij}: Score of indicators j under criterion i, rated on a scale of 1 to 10.

Table 1. Multi-criteria decision matrix for key sustainability indicators (KSI)

Indicator	Relevance (R)	Measurability (M)	Comparability (C)	Influence (I)	Integration (In)	Communication (Com)	Legitimacy (L)	Total Score
Product/component efficiency	9	10	8	10	9	8	9	63
Energy Efficiency	10	9	8	9	9	7	8	60
Material Efficiency	8	8	9	8	8	9	9	59
Systems efficiency	9	7	7	9	8	7	8	55

4. Application of a proactive design for sustainability method in smart factory

The case study (Figure 2) puts sustainable proactive design into practice on an autonomous mobile robot (AMR), integrated into an Industry 4.0/5.0 smart factory. The objective is to reduce CO_2 emissions and improve energy efficiency while ensuring operational performance. This approach is based on the optimization of technical parameters from the design phase: reduction of energy consumption during use (Energy Efficiency), integration of recyclable materials (Material Efficiency) without affecting the robustness of the components (Product/Component Efficiency) and complete life cycle assessment (assembly, use, disassembly) by simulation based on data from IoT sensors and digital twins. This approach allows for better integration and coordination of subsystems, thus promoting real efficiency at the overall system level subsystems (Systems Efficiency). Although the overall methodology includes 8 steps, this section focuses on the 4 most relevant steps applied to the AMR case study.

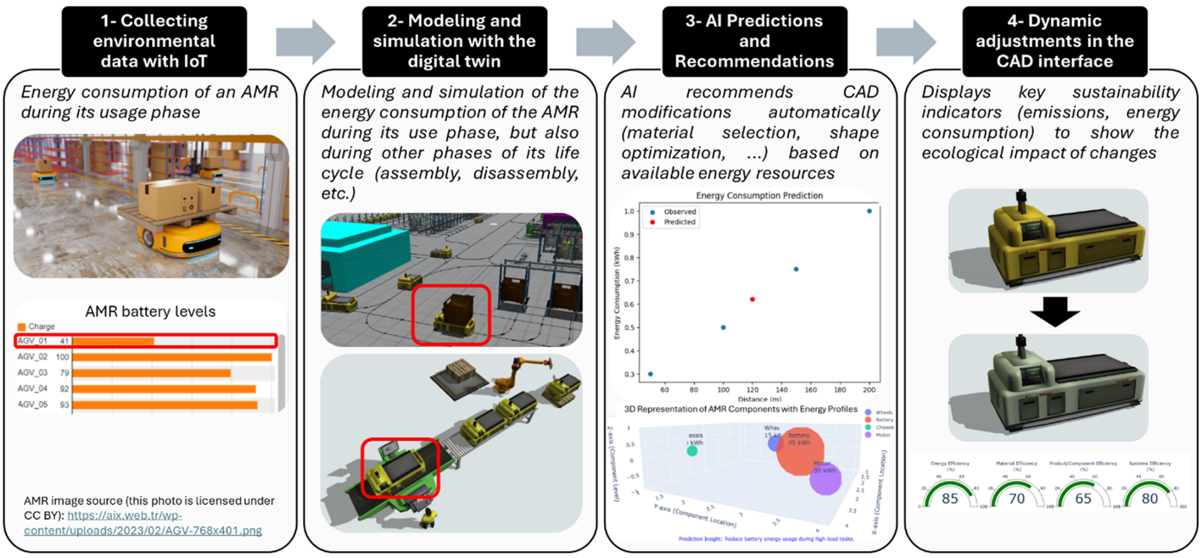

Figure 2. Proactive design for sustainability applied in AMR for smart factory

1. ***Step 1 - Collecting environmental data with IoT (Figure 3):*** The IoT sensors integrated into the AMR record energy consumption during different tasks (e.g. 0.5 kWh for travel tasks at full load and 0.2 kWh in idle mode), battery levels to identify periods of inefficient charging (41% for AGV_01), indirect emissions associated with the use of non-renewable energy sources (e.g. solar power, wind power or fossil fuels from the grid). The collected data is then transmitted in real time to a centralized DTw for analysis.
2. ***Step 2 - Modeling and simulation with digital twins (Figure 4):*** The modeling and simulations carried out with the Flexsim tool allow for the evaluation of the environmental impacts of the AMR during its use and throughout the phases of its life cycle (manufacturing, disassembly, etc.). The data collection assumes that the AMR operates within its manufacturing company, which means that manufacturing and operational data can be directly integrated into the analysis. The

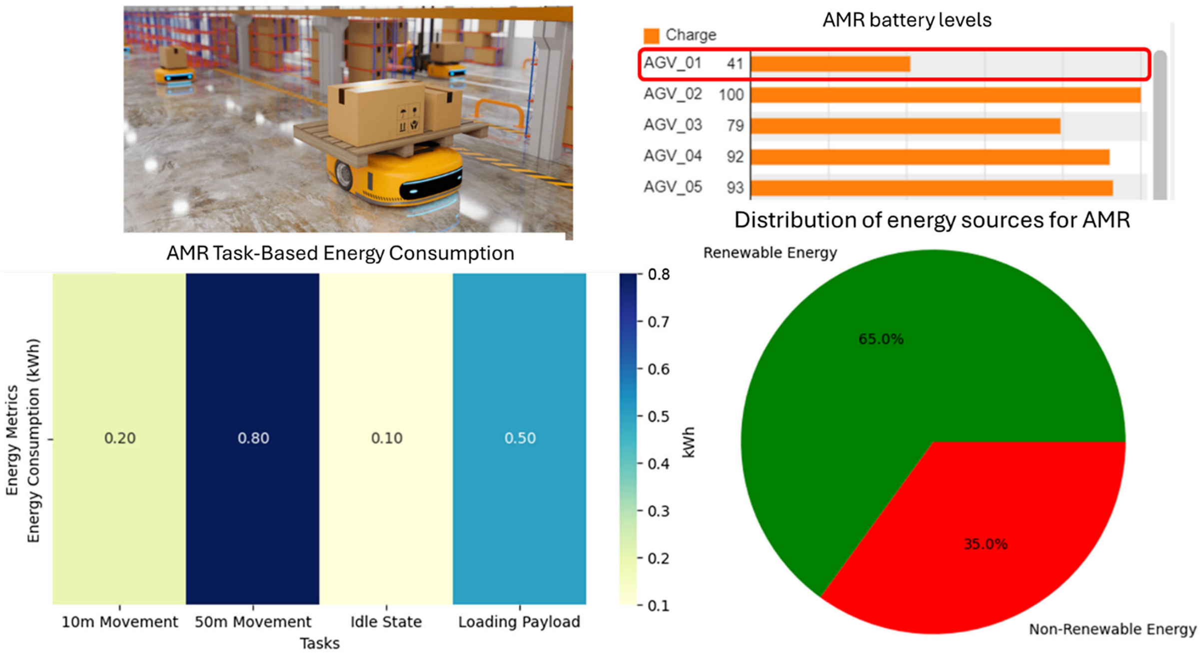

Figure 3. Collecting environmental data with IoT of the AMR

DTw integrates manufacturing data, such as energy consumption and CO_2 emissions, to provide a comprehensive assessment of the life cycle impact. The DTw allows for the representation of the interactions between the AMR and the factory equipment, production tools, and charging stations, in particular. The simulations evaluate factors such as wheel friction, battery choice, and material selection to optimize energy consumption and reduce emissions. Thanks to Flexsim, tasks were simulated over the course of a production day, showing potential energy savings and emission reductions through lightweight or recycled materials, recyclable batteries, or an adjusted wheel geometry to reduce friction resistance.

3. ***Step 3 - AI Predictions and Recommendations (Figure 5):*** The results of the DTw simulations are analyzed by AI algorithms to suggest specific improvements, for example to materials, such

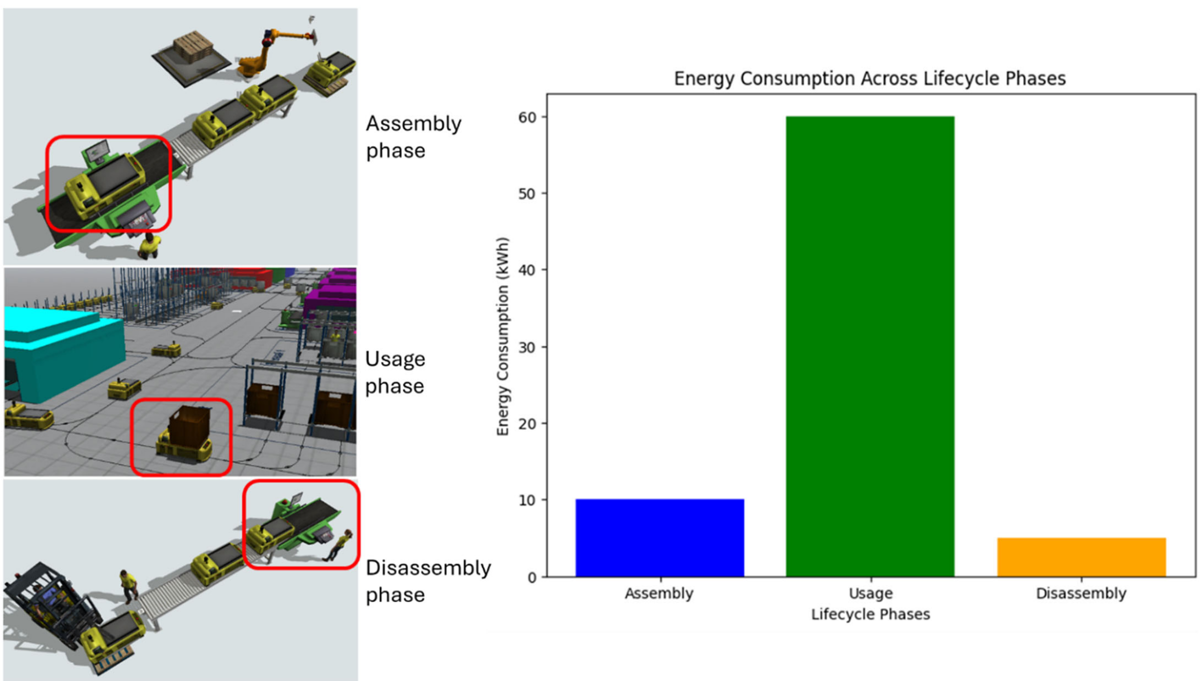

Figure 4. Modeling and simulation with digital twins of the AMR

as replacing aluminium components (e.g. the chassis) with recycled materials to reduce energy consumption and production-related emissions. Another example on task optimization, with the modification of operational parameters, such as reducing sudden accelerations or periods of inactivity to save energy. The use of renewable energies is another example recommended by AI to adapt operating schedules to coincide with periods when renewable energies are available or suggest charging cycles during peak periods of renewable energy production.

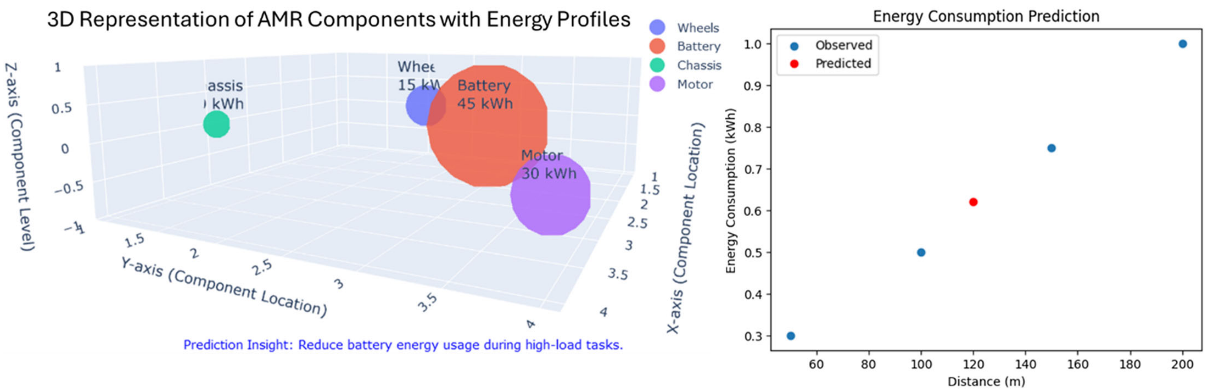

Figure 5. AI Predictions and Recommendations of the AMR

4. ***Step 4 - Dynamic adjustments in the CAD interface (Figure 6):*** The CAD interface displays in real time the four key indicators to guide designers in their technical choices: energy efficiency (kWh/task), material efficiency (% of recycled materials), product/component performance (geometric optimization) and system efficiency (global integration). For example, the gradual addition of recycled materials in the robot led to a significant increase in the share of renewable energy used (in practice increasing from 65% to 85%) while reducing CO_2 emissions by 20 kg per use cycle. Thanks to an immediate update of the data, the impacts of specific modifications – such as the shape of the wheels or their geometry – on energy consumption and overall weight can be quickly assessed. This observation is also consistent with the results obtained by (Gaha et al., 2014) on the interest of such optimizations.

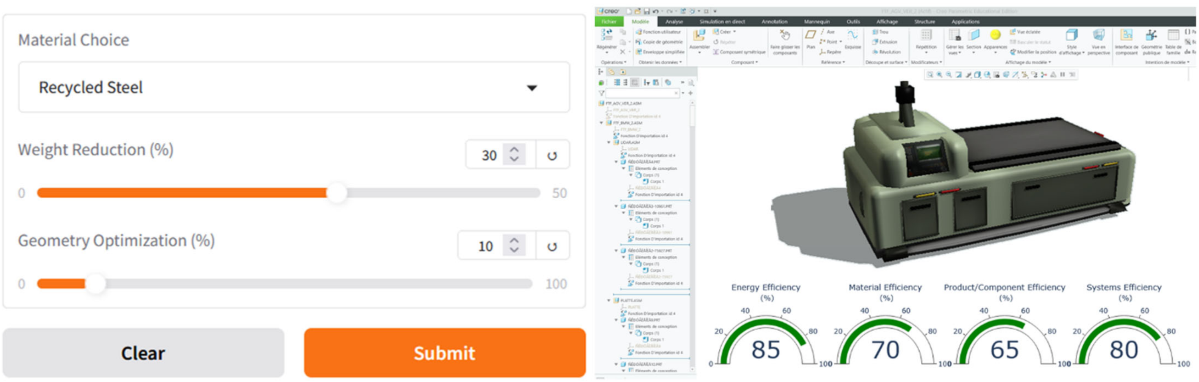

Figure 6. Dynamic adjustments in the CAD interface of the AMR

The AMR was evaluated against four key performance indicators: energy efficiency, material efficiency, product/component efficiency and system efficiency. CAD optimization was used to adjust the choice of recycled materials (recycled steel) and adapt geometry to reduce weight and minimize wheel friction, thus improving energy efficiency. What's more, adjusting operating cycles according to renewable energy peaks has reduced CO_2 emissions. The integration of digital twins and IoT data validates the feasibility of a proactive approach to optimized sustainable design decision-making, paving the way for its application to other sectors.

5. Discussions on challenges and limitations

5.1. Challenges observed in the case study

The application of the proactive approach in sustainable design, illustrated here by the practical case of the AMR, highlighted several technical difficulties linked to integration into the CAD environment.

1. ***Complexity of data integration:*** Direct exploitation of data from IoT sensors requires particularly precise models, which implies high computing power and generates constraints on transmission fluidity and processing speed. Simplifying data flows and optimizing calculation methods could help to better manage these operational difficulties.
2. ***Variability of energy resources:*** The dependence on intermittent renewable energy sources (solar, wind) has resulted in real operational constraints when optimizing AMRs. In this regard, advanced predictive models would allow anticipating variations in available energy, thus improving the coordination of tasks according to real energy resources.
3. ***Selection and standardization of key sustainability indicators:*** Despite the structured approach by multi-criteria indicators, the variable weighting according to industrial sectors still constitutes an obstacle to their uniform adoption. As Saiga et al. (2021) point out, the development of clearly standardized reference frameworks, like sustainable reverse engineering approaches, would greatly facilitate the concrete and broad integration of KSIs into design processes (Saiga et al., 2021).

5.2. Wider limits

Beyond the specific difficulties observed in the case of AMR, several more general obstacles could limit the large-scale adoption of proactive design methods for sustainability:

1. ***Cybersecurity vulnerabilities:*** The simultaneous connection of IoT, AI and DTw systems potentially increases cybersecurity risks. Intentional alteration of data, for example on lifetime or performance, could lead to inadequate design choices. The systematic introduction of robust encryption and anomaly detection mechanisms is then essential.
2. ***Engineering skills gaps:*** Effective integration of these new technologies requires advanced knowledge in AI, digital twins and environmental assessment. However, these multidisciplinary skills remain uncommon in today's companies. To fill this gap, the establishment of suitable training through close cooperation between universities and manufacturers now seems essential.
3. ***Implementation costs:*** Implementing IoT-based solutions often generates technical complexity and high costs, especially for SMEs, potentially widening the digital divide. A phased integration strategy, tailored to each company's specific technical capabilities, would facilitate access to these sustainable methods on a broader scale.

6. Conclusion and future work

6.1. Summary of the contributions of proactive design for sustainability in Industry 4.0/5.0

Proactive design for sustainability is an approach that uses recent technological tools such as digital twins, artificial intelligence and IoT sensors. These tools allow designers to directly improve their technical choices while respecting environmental constraints and reducing overall energy consumption. The main objective of this method is to reduce environmental emissions of products while ensuring their economic viability and operational efficiency in an industrial context. The proposed methodology was applied to a case study of an autonomous mobile robot in a smart factory. Energy efficiency was optimized by adjusting parameters and managing renewable resources, the use of recycled materials limited the exploitation of resources, while the modification of components reduced wear and maintenance. Finally, the coordination of subsystems improved overall efficiency, adaptable to various industrial sectors. The example developed in this study around the AMR robot shows the potential of this method in other industrial sectors, thus facilitating the simultaneous consideration of environmental, economic and operational objectives.

6.2. Research prospects

To meet these challenges, several avenues seem relevant to explore:

1. ***International standards and regulations:*** It appears essential to define homogeneous and applicable benchmarks in various industrial sectors, to guarantee consistent use of KSI directly within design tools.
2. ***Securing environmental data:*** It's also necessary to continue the search for robust security mechanisms capable of effectively protecting IoT sensor data, thus avoiding any risk of manipulation or cyber-attack that could compromise their reliability.
3. ***Training and skills development:*** The development of specific training courses, integrating both new approaches in ecodesign and recent advances in AI technologies and digital twins, appears essential to compensate for the current lack of expertise in industry.
4. ***Sectoral extension:*** Finally, the establishment of clear and harmonized benchmarks for KSIs in various sectors (e.g. automotive, aeronautics, or electronics) and their progressive extension to other industrial fields could greatly facilitate their widespread adoption, thus making the proactive design approach for sustainability truly accessible.

Proactive design for sustainability is an integrated and adaptable approach that can help transform industrial practices by aligning economic goals with ecological imperatives. Resilient and sustainable factories that comply with Industry 4.0/5.0 principles can be created through sustained research.

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