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Product Structural Complexity and Sustainability Impact: A Design Structure Matrix Approach

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Abstract: Sustainable design has gained high importance over the past decade due to global environmental concerns. Various design of sustainability (DfS) tools are available; however, their adoption is limited mainly due to their lack of integration and holistic approach. This research integrates product structural complexity and sustainability assessment methods to find sustainable design strategies. The structural complexity of the product is captured by automatically generating a design structure matrix from the product CAD model. The influence and propagation index captures each component's local and global influence within the product structure. The sustainability assessment for each component is conducted using life cycle assessment, and an opportunity score is proposed to find the components with high sustainability impacts and low systemic risks to the design. The sustainable design strategies are investigated through evaluation of environmental impacts of these components. The application of this framework is demonstrated through a robotic arm case study.

Keywords: Design Complexity, Design Structure Matrix, Design for Sustainability, Sustainable Design Strategy

1 Introduction

The current global environmental concerns have been growing over the past decade and have resulted in a high rate of sustainability research. Various industries and companies have aimed to achieve sustainability in their organizations and products by implementing sustainable design tools. The growing societal awareness regarding sustainability has made international organizations and agencies focus on sustainable development and policies to protect and promote a sustainable future. Seventeen sustainable development goals (SDGs) have been highlighted by the United Nations (UN) 2016 report (United Nations, 2016). These goals are designed around the triple bottom line (TBL) concept, which defines sustainability holistically considering people, planet, and profit (Elkington, 1999). Sustainable product design can significantly contribute to achieving these goals, specifically SDG 12, which addresses "sustainable consumption and production." In sustainable design research, the objective is to provide practical and effective tools and methods that can be implemented to address the current challenges of sustainable design systematically. Researchers have found that approximately 80% of products' sustainability impact could be considered and managed in the design phase (Lewis et. al, 2017 and Kulantunga et. al, 2015).

Researchers have proposed numerous sustainable design tools and methods in recent years (Ahmad et. al, 2018). Design for X (DFX) methods have long aimed to integrate considerations like manufacturing, cost, and assembly early in the design phase, with subsets such as design for environment (DFE) and design for sustainability (DFS) pushing for environmental practices (Kuo, et. al, 2001). While recent years have seen an increase in tools like eco-design, SDMTs, and environmental assessment methods, actual adoption among designers remains limited due to a lack of practical, business-relevant frameworks. DFX tools are typically narrow in scope, emphasizing economic factors and treating life cycle phases in isolation (Rousseaux et. al, 2017). Life cycle assessment (LCA) has achieved broader use due to ISO standardization (ISO 14044, 2006), yet designers face challenges in extracting actionable insights from LCA data, mainly because the tools fail to connect product architecture with process requirements.

To address the challenges in current methods and tools for sustainable product design, this study proposes a novel framework that integrates product structural complexity and sustainability impact to find sustainable design strategies. The structural complexity of the product is demonstrated by utilizing the design structure matrix (DSM) to find the importance of each component within the product's architecture. The LCA is utilized to find the environmental impacts of each component. Utilizing this component-level information, the most effective sustainable design strategies are found. In this research, the sustainable design strategy is defined as a systematic method of design intervention that can effectively reduce the product's environmental impacts with minimal risk to the product structure or functionality. This research aims to answer the following questions: What mechanisms can integrate structural complexity and network-based metrics with sustainability assessment? What component-level characteristics indicate high sustainability impact and low systemic risk, and what criteria prioritize them for design improvement? The following sections outline the background and describe the methodology proposed. A robotic arm case study is selected to illustrate the application of the proposed method.

2 Background

One of the most established tools for examining how changes propagate through a system is the design structure matrix (DSM) (Brahma & Wynn, 2023). A DSM captures the relationships and interdependencies between components, modules,

or subsystems in a straightforward matrix format (Sharman & Yassine, 2004). Rows and columns represent system elements, and the cells indicate functional, physical, or informational dependencies. DSMs are valued for exposing design problems, reducing unnecessary complexity, and improving system architecture. Unlike sprawling network diagrams, DSMs are compact and scale well for large systems (Eppinger & Browning, 2012). Techniques like partitioning and clustering are commonly used to cut down feedback paths or isolate independent clusters of components (Sharman & Yassine, 2004). These methods can reorder the matrix based on predefined dependencies or custom logic (Eppinger & Browning, 2012).

Life cycle assessment (LCA) is a well-established method for evaluating the environmental impacts of products and processes across their entire life cycle, from raw material extraction to disposal (Barahmand & Eikeland, 2022). Its broad use across industry and academia highlights its strengths and limitations in informing environmentally responsible design and decision-making (Fauzi et al., 2019; Rodriguez et al., 2020). The ISO 14044 standard lays out four core phases of an LCA: goal and scope definition, life cycle inventory (LCI), life cycle impact assessment (LCIA), and interpretation (International Organization for Standardization, 2006). In the first step, the analyst defines the system boundary, identifies which stages to assess, and determines the functional unit—the measure used for fair comparisons. This includes mapping upstream and downstream product flows, from material extraction and manufacturing to use and disposal, and organizing them into a process tree.

The inventory analysis stage collects input-output data for each life cycle phase, including energy, materials, water use, and emissions. Primary data are measured directly but are resource-intensive; secondary data are taken from databases and literature, offering quicker access but often less precision. These flows are calculated relative to the functional unit and aggregated across the process tree. The impact assessment phase interprets this data to quantify environmental impacts. A commonly used method is ReCiPe, which categorizes impacts into midpoints (e.g., climate change, acidification) and aggregates them into endpoints like damage to human health, ecosystems, and resource availability (Huijbregts et al., 2016). These are expressed in DALYs, species loss over time, and monetary costs, respectively. ReCiPe also provides interpretive perspectives—individualist, hierarchist, and egalitarian—to reflect different value systems.

The final phase is interpretation, synthesizing results, identifying critical issues, and recommending improvements. Despite its depth, LCA remains difficult to integrate into early design processes. One significant barrier is its poor alignment with how product structures and lifecycle processes are linked (Kota & Chakrabarti, 2010). Designers often find LCA results too abstract or uncertain to guide meaningful trade-offs. Regulatory compliance pressures also shape how LCA is used—typically with a cost-minimization mindset (Whitefoot et al., 2017). Some researchers argue that LCA is more useful as a specialized tool for strategic concept evaluation, not specific design practices (Millet et al., 2007). Many sustainable product design tools still fail to consider the full sustainability dimensions of environmental, social, and economic impact (Ahmad et al., 2018). Attempts to integrate LCA into CAD tools have resulted in significant inaccuracy (Morbidoni et al., 2011). Hybrid LCA methods combining process and input-output analysis have been proposed (Lenzen & Crawford, 2009); however, experts debate their reliability (Pomponi & Lenzen, 2018; Yang et al., 2017).

DSM and LCA have been combined previously to find the environmental impacts of design decisions within a product system (Carter et. al, 2022; Basereh Taramsari, et al, 2023). The multi-domain matrix and LCA have also been used to map the dependencies between designs and create a holistic sustainable design framework that enables simultaneous consideration of a product's social, economic and environmental impacts and finds optimized sustainable solutions (Basereh Taramsari, et al, 2025). However, applying this method to complex engineering design systems has various challenges and requires a more strategic approach. Researchers have proposed a network-based structural complexity metric for system architectures that includes complexities of system components, connection among components, and topological complexity (Sinha & de Weck, 2013; Sinha & de Weck, 2016). Spectral structural complexity metric is another method that utilizes the eigenvalues of the system of interest as a graph (Pugliese & Nilchiani, 2019).

3 Methodology

This section describes the research framework's methodology, shown in Figure 1. This framework is designed to provide a holistic approach toward complex engineering systems and find the most effective sustainable design strategy based on the structural complexity of the product and its sustainability impact. The proposed framework has three phases: structural complexity, sustainability assessment, and system improvement. It loops back to CAD data with each iteration of design improvement. This framework is implemented using Python programming language to automate the process, and it aids designers in understanding the state of their product and balancing sustainability metrics against structural complexity. Each phase of the framework is described in the following sections.

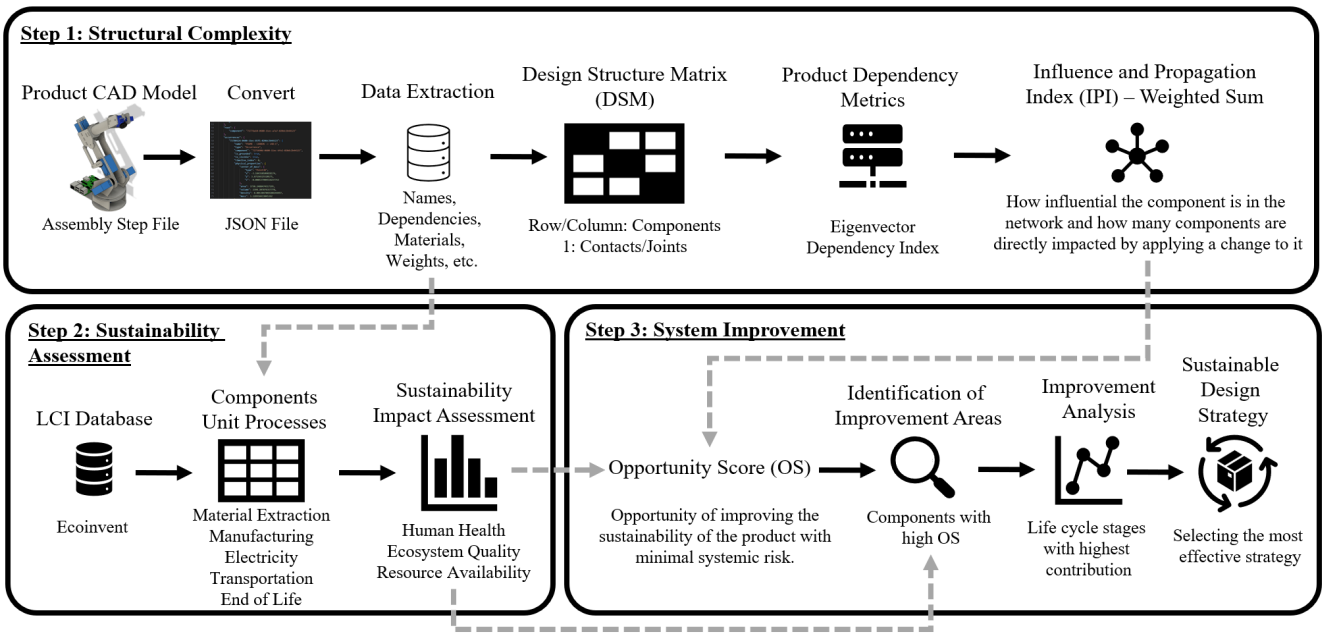

Figure 1. Research Methodology

3.1 Structural Complexity

In the structural complexity step of the framework, the existing product's CAD model (usually a STEP file) is converted to a JSON library file format. This structured text file translates CAD elements like geometry, metadata, and components into a machine-readable format for software applications. These metadata include the hierarchy of the sub-assemblies, components, names of components, bodies, mass, contacts/joints, center of mass, material categories, density, area, volume, etc. The relevant data utilized in this framework are the names of components, their mass, material category, and their structural dependencies. Components and their dependencies create a product design structure matrix (DSM) where the components are represented in rows and columns, and the structural dependencies (contacts/joints) between them are identified in the matrix. Then, product dependency measures are adopted to identify the most critical components in DSM. Dependency index determines the most structurally connected components based on the number of direct dependencies they have with other components. This measure reflects the immediate structural influence of a component within the network and serves as the foundation for more advanced analyses in this framework. The DSM is primarily used in product architecture design; however, this framework requires the final design's details to construct the matrix.

Let D be a binary DSM representing a system of n components, where each element d_{ij} denotes a direct dependency of component i on component j. The dependency index $C_{dep}(i)$ of component i is defined in Equation 1.

$$C_{dep}(i) = \sum_{j=1}^{n} d_{ij} \qquad (1)$$

Here the d_{ij} is the (i,j)th element of the DSM, defined in Equation 2.

$$d_{ij} = \begin{cases} 1 & if\ component\ i\ depends\ on\ component\ j \\ 0 & otherwise \end{cases} \qquad (2)$$

This metric captures the number of direct outgoing dependencies for component i, indicating how many other components are directly impacted when a design change is applied. This DSM-based system modeling reflects a component's structural complexity or coupling based on its immediate upstream requirements. To normalize the dependency index, it can be divided by the theoretical maximum number of dependencies as shown in Equation 3.

$$C_{dep}(i)\ norm = \frac{C_{dep}(i)}{n-1} \qquad (3)$$

While the dependency index quantifies local complexity based on direct connections, a more holistic view of systemic influence can be captured using eigenvector centrality. This approach assigns relative scores to components such that connections to highly dependent components contribute more to the component's score as defined in Equation 4.

$$C_E(i) = \left(\frac{1}{\lambda}\right) \sum_{j=1}^{n} d_{ij} \cdot C_E(j) \qquad (4)$$

This metric can also be represented in vector form as shown in Equation 5.

$$D \cdot x = \lambda \cdot x \qquad (5)$$

where D is the DSM matrix, x is the eigenvector of centrality scores, and λ is the corresponding eigenvalue. The eigenvector associated with the largest eigenvalue (i.e., the principal eigenvector) is used to compute the final scores.

A composite metric named Influence and Propagation Index (IPI) is proposed by combining the dependency index and eigenvector centrality to capture each component's local and global importance within the system architecture. This metric integrates the effects of direct structural dependency and systemic influence. The IPI for a component i is defined in Equation 6.

$$IPI(i) = w_D \cdot C_{dep}(i) + w_E \cdot C_E(i) \qquad (6)$$

where w_D and w_E are the respective weights assigned to the normalized dependency index and eigenvector centrality. Equal importance is assigned to both components by setting $w_D = w_E = 0.5$. Here, $C_{dep}(i)$ denotes the normalized dependency index of component i, and $C_E(i)$ denotes its normalized eigenvector centrality. The IPI provides a balanced measure for immediate dependency structure and a component's broader influence within the DSM network.

3.2 Sustainability Assessment

Life cycle assessment is utilized as a sustainability assessment tool to evaluate the potential environmental impacts of each component within the system. In the second step of the framework, the material categories extracted from the JSON file and other component information guide the grouping of the activities included in the Ecoinvent dataset (Ecoinvent, 2025). The grouping consists of multiple unit processes associated with each life cycle phase of the component: material extraction, manufacturing, electricity, transportation, and end-of-life. The use phase of the components was intentionally neglected in this method because individual components do not have a specific use phase, and this phase should be considered at the product sustainability assessment level. The possible activities associated with each category are collected to create a unit processes dataset that can be utilized for life cycle assessments. The product data is used to find the material, manufacturing process, electricity, transportation, and end-of-life. This step helps to construct a component life cycle system that provides a platform to utilize the unit processes dataset (collected from Ecoinvent).

Life cycle assessment method follows a matrix-based LCA. The technology matrix (A) is generated using the inputs and outputs of the product system, which are defined based on unit processes aligned with the goal and scope of the study. The values assigned to each flow are determined using the extracted CAD data equations. The functional unit of the product is used to construct a reference flow matrix, also known as the demand matrix, denoted as *f*. Given that both *A* and *f* are known, the scaling factor matrix *s* is calculated using Equation 7 (Heijungs and Suh, 2002).

$$s = A^{-1} \cdot f \qquad (7)$$

The life cycle inventory (LCI) data are then organized into the environmental intervention matrix *B*. These data are sourced from the Ecoinvent database, and the inventory matrix g is computed using Equation 8.

$$g = B \cdot s \qquad (8)$$

The characterization factors (CF) matrix, denoted Q_c, is obtained from the ReCiPe 2016 midpoint hierarchist (H) life cycle impact assessment (LCIA) method. After the inventory matrix g is categorized according to each impact category for each unit process, the resulting environmental impact matrix h is defined in Equation (9).

$$h = Q_c \cdot g \qquad (9)$$

The matrix h includes 18 midpoint indicators, which are further classified into three endpoint categories defined by the ReCiPe methodology. The endpoint CFs are also based on the hierarchist perspective. These endpoint categories aggregate the midpoint indicators into three overarching areas of protection: disability-adjusted life years (DALY), species loss measured in species.years, and resource use expressed in monetary terms (USD). Identifying the maximum midpoint impact within each endpoint category makes it possible to determine which unit process contributes most significantly to each protection area. Normalization and weighting are optional steps that allow further aggregation of these impacts into a single score. This score is measured in eco-indicator points (Pt), representing the average world citizen's annual environmental impact share from the year 2010. The weighting applied in this study also follows a hierarchical perspective, assigning weights of 400 to the ecosystem category and 300 to the human health and resource depletion categories. Although normalization and weighting introduce additional uncertainty and are subject to methodological limitations, they help derive a single environmental sustainability score.

3.3 System Improvement

The $SI(i)$ denotes the previously assessed sustainability impact score for component i, which is a normalized value. This value captures the negative sustainability impacts of the component across human health, ecosystem quality, and resource availability. To identify components within the system architecture that offer the most significant potential for sustainability improvement while minimizing the risk of change propagation and systemic disruption, an Opportunity Score (OS) is defined for each component i as shown in Equation 10.

$$OS(i) = SI(i) \cdot (1 - IPI(i)) \qquad (10)$$

This metric combines the assessed sustainability burden of a component with its structural influence, as quantified by the Influence and Propagation Index (IPI). A higher Opportunity Score indicates a component that contributes significantly to sustainability concerns yet holds relatively low systemic risk, thereby representing a promising candidate for intervention with reduced architectural change propagation effects. This system will identify components that offer the most significant opportunity for sustainable improvement with minimal system-wide consequences. The following steps are the identification of improvement areas and improvement analysis to evaluate the effects of the implemented methodology on achieving sustainability goals within the design systems studied. This process begins by ranking all product components based on their Opportunity Scores, which reflect the potential for sustainability improvement relative to systemic risk. The top components with the highest scores are selected for further investigation. LCA results of this component are examined to identify the environmental impacts across different stages, focusing on human health, ecosystem quality, and natural resource depletion. The life cycle stages with the highest impacts are identified as critical. The associated unit processes are analyzed within each of these critical stages to assess inputs, energy usage, and emissions. This analysis identifies the specific contributors to the environmental burden. Targeted improvements are proposed based on these findings, including substituting high-impact materials, enhancing process efficiency, and eliminating harmful outputs through redesign. The outcome is a report highlighting the most impactful components, the critical life cycle stages they influence, and detailed, process-level recommendations to guide sustainable design improvements.

3.4 Case Study

An industrial robotic arm was selected as a case study to demonstrate the framework's application. This case study represents a highly complex system architecture required to test the limits of this framework. The robotic arms data was extracted from the Assembly Dataset Fusion 360 Dataset (Autodesk, 2021), a comprehensive collection of engineering design data comprising 8,251 distinct assemblies and 154,468 individual parts. These parts can be organized into components, which represent reusable design elements, and are either individual components like screws or sub-assemblies composed of multiple components. Components can be positioned in global coordinates and interconnected using joints to represent physical relationships. The dataset is provided in various data formats, including B-Rep and mesh formats for geometry, with JSON text files containing parameter information. Each element in the dataset is cross-referenced using universally unique identifiers (UUIDs). The data set includes information about assembly hierarchies, joint motions, contacts, holes, and other physical properties. The data set is standardized in centimeters for all units, including geometry and distance parameters, while angular units are in radians. This rich data set is organized and structured following the Fusion 360 API, making it a valuable resource for research and applications related to engineering design. An industrial robotic arm shown in Figure 2 is selected as the case study to show a highly complex engineering system with 40 components. The research framework (Figure 1) proposed in this study is applied to the robotic arm, and the results obtained from this analysis are presented in the following sections.

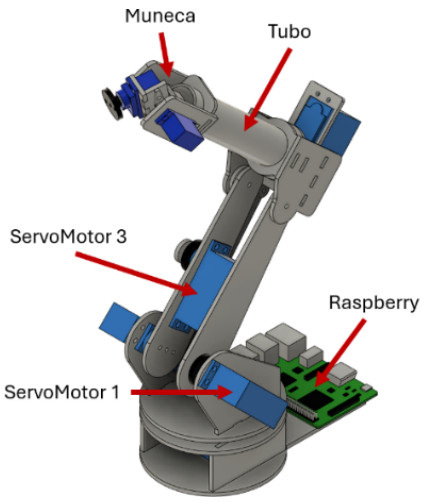

Figure 2. Robotic arm case study

The data extracted underwent a data cleaning process to prepare the data for the analysis proposed in this framework. It involves various steps, such as pre-processing, handling missing data, removing duplicates to maintain data integrity, and detecting and treating outliers that can skew analysis to ensure data is in a usable format. The process also includes addressing inconsistent data and removing redundant information. Text cleaning ensures text descriptions and labels are standardized and free from irrelevant characters or typos. Different parts of the JSON file structure were used to extract this information. Most features are saved as float and integer values, and features such as material categories and industries are user-defined elements. The material categories are classified into seven categories defined by users. These materials are used to construct a life cycle system for each component within the product to evaluate the sustainability impacts previously discussed. Necessary assumptions were made to estimate the sustainability impact of each component, and most likely, materials and processes were assigned to each element.

4 Results

The JSON files included the dependencies between components within the product hierarchy, and the robotic arm displays a complex modular architecture. These dependencies were utilized to automatically generate the DSM of the robotic arm, as shown in Figure 3. The DSM shows this product comprises numerous modules arranged in a deeply branched configuration, including servo motors, joints, and base components. The low density in this product architecture indicates a fragmented architecture that provides many functional advantages but may also introduce manufacturing complexity and resource intensity.

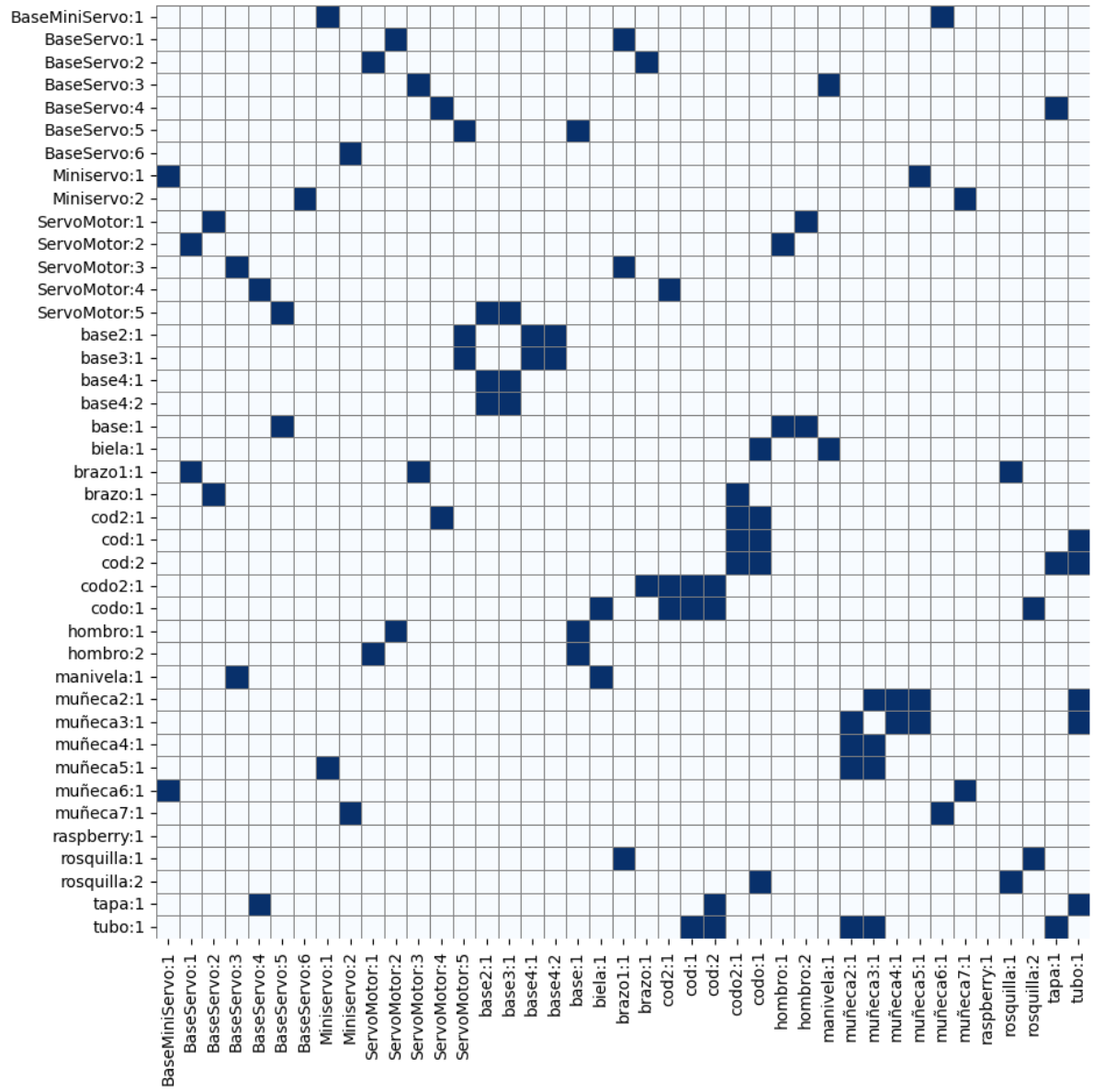

Figure 3. Design structure matrix (DSM) of robotic arm

The DSM is used to find each component's dependency index and eigenvector values, and equation 6 was used to determine each component's influence and propagation index. Figure 4 shows the components of this product architecture with the highest IPI values. The tubo:1 and multiple joint components (muñeca2:1, codo1:1, etc.) emerge as key influential components, indicating their local and global importance within the product system. The broad distribution in IPI values shows many critical components in this product system where applying change would initiate risk to the overall system structure. High IPI values are distributed across proximal (base and shoulder) and distal (wrist and tube) modules, reinforcing the system's complexity and interdependence. This suggests that design modifications to these central nodes may ripple extensively across the product. On the other hand, the servo motors have the lowest IPI value within this system.

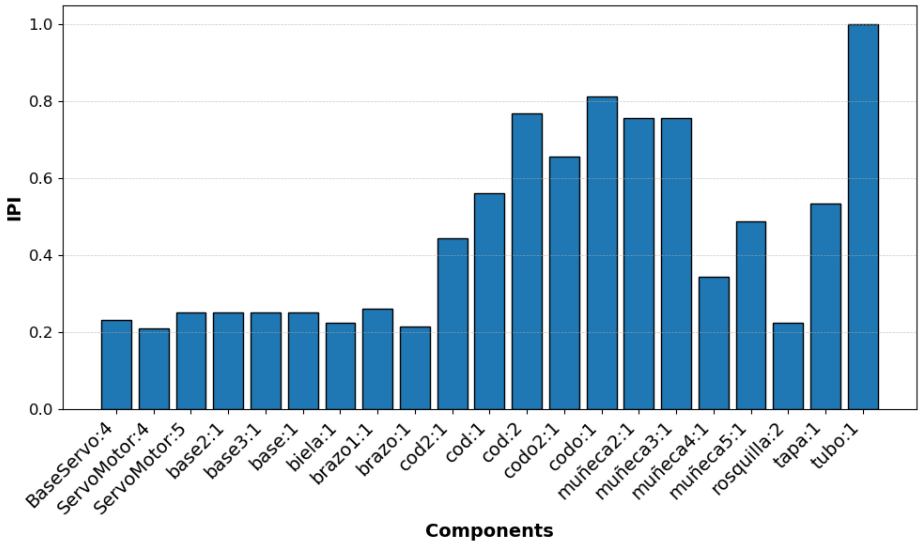

Figure 4. Influence and Propagation Index (IPI) of the robotic arm's components

The sustainability assessment phase of the methodology was implemented utilizing the LCA methodology described, and its results are illustrated in Figure 5. This shows the ServoMotor:3 has the highest negative environmental impact compared to the other components in this product, followed by ServoMotor:1, 4, and 5.

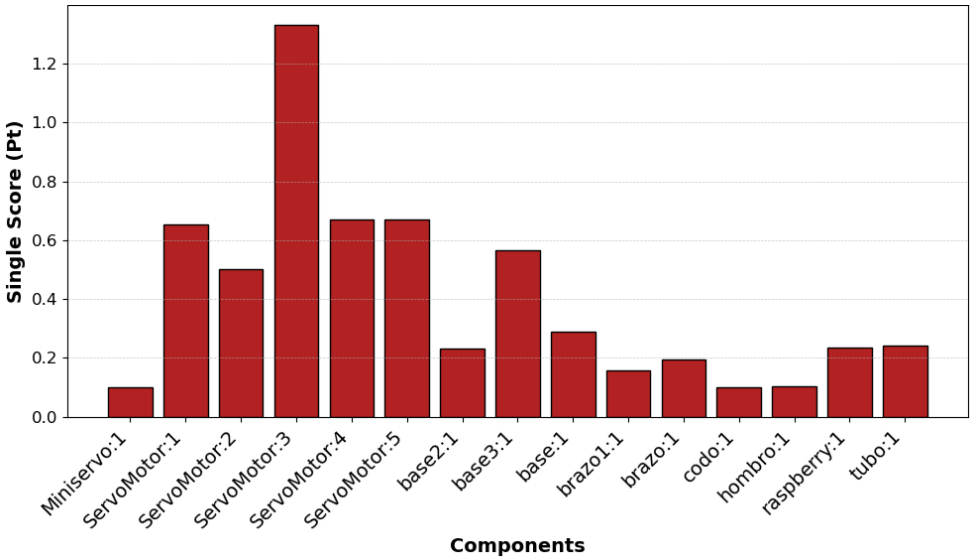

Figure 5. Sustainability impact of the robotic arm's components

The next phase includes system improvement, and opportunity scores for each component are calculated using Equation 10. The results of the opportunity scores are shown in Figure 6. ServoMotor:3 has been identified as the component that provides the highest opportunity to improve the product's sustainability with minimal systemic risk. The position of this component within the product structure and its dependencies are demonstrated in the DSM. It has the lowest local and global importance within the product system, and considering its high sustainability impact, this component is selected to find sustainable design strategies.

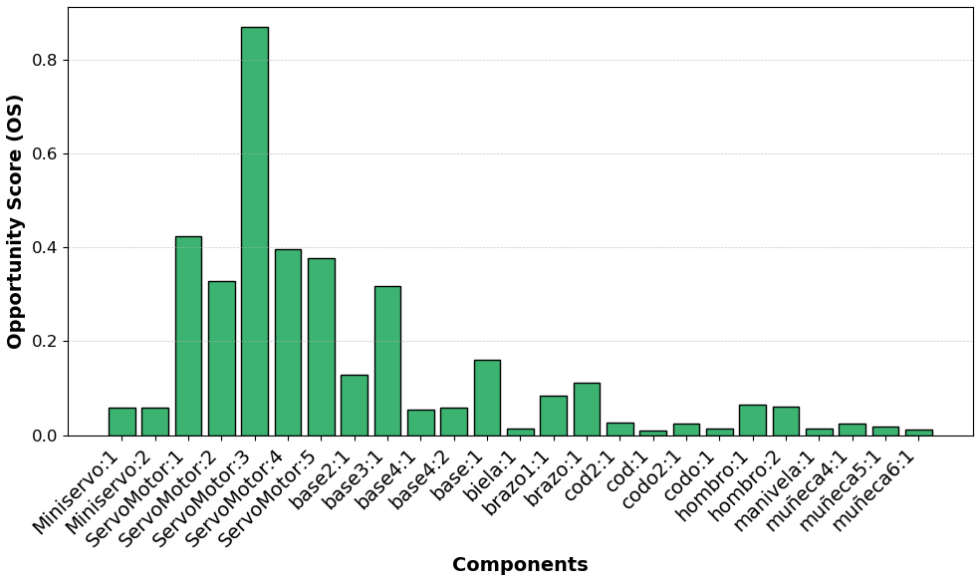

Figure 6. Opportunity scores (OS) of robotic arm's components

Focusing on the LCA results of the ServoMotor:3, the material extraction phase of the component has been found to have the highest contribution to all three endpoint categories of ecosystem quality, Human health, and natural resources availability. Figure 7 shows the highest contributing life cycle stages of this component. Based on the results obtained from this analysis, the unit processes used in this component's material extraction life cycle stages need to be analyzed, and various strategies can be implemented, such as sustainable material alternatives or topology optimization, to reduce the amount of material used in this component.

Figure 7. Highest contributing life cycle stages of ServoMotor: 3

5 Discussion

The robotic arm case study demonstrated the application of the proposed framework and revealed the component-level variations in environmental performance and systemic influence. The results highlighted the framework's capabilities to identify components with a high ecological burden that are systemically isolated and identify them for redesign or modification opportunities within the system. The OS metric strategically combines components' structural importance and sustainability impact to prioritize impactful and low-risk design changes. The case study findings offer direct implications for sustainable design interventions.

The proposed framework advances sustainable design practice by integrating structural complexity analysis with life cycle assessment, enabling an intuitive and traceable design decision process. This framework utilizes DSM to quantify design interdependencies through eigenvector and dependency index and formulate a system-aware prioritization mechanism

through the IPI metric. Through this structured integration, the designers can gain quantitative feedback on which components to target with a clear justification of the reasoning behind those decisions. The closed-loop improvement mechanism, informed by the system architecture and sustainability data, supports iterative design strategies where component-level interventions can be optimized based on environmental leverage and structural dependencies.

In addition, the framework approach streamlines a typically siloed design process by connecting CAD-level dependencies (via assembly step files and JSON extraction) to LCA datasets (via Ecoinvent-based unit processes). This methodological bridge offers a practical and scalable means for engineering teams to embed sustainability within advanced product architectures, particularly in mechatronics, consumer products, and aerospace sectors with high structural complexity.

Considering the advantages of this framework, it has limitations that need to be recognized. It is mainly suited for detailed design or redesign phases, where complete product models and bill-of-materials are available. This provides challenges in applying this framework to early conceptual stages lacking component-level detail. Its dependence on static LCA databases introduces uncertainty, specifically with emerging materials or region-specific supply chains. The Opportunity Score condenses systemic risk into a single metric, aiding prioritization but failing to capture non-linear or functional dependencies in the product system. Future research can integrate social and economic aspects of sustainability, implement multi-objective optimization, and embed uncertainty quantification in LCA to improve utility and scalability. Broader validation across diverse products and life cycle contexts is also required to evolve the framework into a robust decision-support tool that helps designers navigate the complex structure, function, and sustainability interdependencies.

6 Conclusion

The framework proposed in this research study addresses the current challenges of sustainable design tools by integrating product design structural complexity with sustainability assessment methods. The framework contributes to the current design for sustainability tools by expanding the contributing factors and providing a feasible design strategy. The Influence and Propagation Index (IPI) and sustainability impact values resulted in the Opportunity Score (OS) formulated to help designers identify the most effective and low-risk design strategies. The framework's application was demonstrated using an industrial robotic arm as a case study, and the results provided valuable insights.

The proposed framework in this research presents a systems-level strategy for integrating structural complexity into sustainable product design. The framework provides a holistic and actionable method for sustainable design strategies by linking data from CAD models and LCI databases through a network-based analysis. This approach improves upon conventional LCA and eco-design tools by enabling system-aware change propagation modeling and advances the practical application of systems thinking in engineering design. The framework lays the groundwork for future integration of optimization, uncertainty modeling, social, and economic sustainability metrics. It represents an essential step toward equipping product designers with the tools and insights to navigate the interdependencies between structure, sustainability, and systemic design change.

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