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An automated workflow for integrating environmental sustainability assessment into parametric part design through standard reference models

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A R T I C L E I N F O

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A B S T R A C T

Integrating environmental sustainability assessment into parametric design presents an opportunity for enabling sustainable product design. However, this is a challenging task as quantitative methods for sustainability assessment are poorly integrated with parametric design and optimization tools. Furthermore, current streamlined approaches for computing environmental impact during the design stage often ignore manufacturing-related impacts resulting from the geometric complexity of parts. To address these gaps, we present a systematic workflow for computing environmental indicators from parametric design models. Our workflow utilizes the unit manufacturing process information model to evaluate manufacturing-phase resource consumption from process planning data, and consequently enables quantitative correlation of design parameters to the calculated environmental indicators. We demonstrate our workflow through a case study involving the design of a rigid flange coupling, wherein we evaluate the influence of geometric design parameters on the corresponding environmental impact of the design.

1. Introduction

A significant portion of a product's life cycle environmental impacts are committed during the design stage (Ramani et al., 2010). This is especially true for mechanical parts as their life cycle environmental impacts are primarily a function of material, geometry, and attributes that are fixed at the design phase. However, assessing such impacts during the design stage is challenging due to the limited availability of downstream life cycle information (Brundage et al., 2018). Consequently, a wide range of qualitative and semi-quantitative tools are used to guide the ecodesign process (Ramani et al., 2010). With the ubiquity of sensing capabilities relevant for characterizing environmental sustainability throughout the production process (Stock and Seliger, 2016), more quantitative approaches are possible.

Creating quantitative methods in design decision-making, e.g., incorporating results from streamlined life cycle assessment into parameter selection or optimization, requires (i) estimating downstream life cycle information (e.g., energy consumption in manufacturing) empirically or (ii) analytically quantifying variation in environmental impact as an explicit or implicit function of design parameters. Research that focus on the former area often use information from similar existing designs to predict the environmental impact of the new designs (Bernstein et al., 2010; Eisenhard et al., 2000; Ramanujan et al., 2015). In the latter case, design parameters can be used to construct parametric life cycle inventories, which in turn enable designers to explore relationships between specific design parameters and the resulting environmental impact. Note that most streamlined methods, e.g., SolidWorks SustainabilityX-

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press[1], scale such inventories volumetrically, i.e., with the volume of the part or the volume of the material removed in subtractive manufacturing processes. Hence, they do not account for variation in manufacturing processes resulting from geometric complexity. Furthermore, data from downstream stages, e.g., machine-reported data from production systems needs to be represented through standard representations and interfaces that are useful for design decision-making. Although standards activities and reference implementations are well underway for addressing such needs (see Sec. 2), to the best of the our knowledge, there is no published previous research on standards-based approach for computing and representing life cycle inventories such that can be linked to design data, e.g., computer-aided design (CAD) models.

This paper focuses on creating a systematic workflow for computing environmental performance indicators from parametric design models. The developed workflow utilizes the unit manufacturing process information model to evaluate manufacturing-phase resource consumption from process planning data and consequently enables quantitative correlation of specific design parameters to environmental performance indicators from downstream life cycle stages. The primary contribution here is a proof-of-concept workflow for performing sensitivity analyses of design attributes via ASTM E3012 (ASTM E3012, 2020) demonstrated through a case study of a rigid flange coupling.

2. Background and related work

The basis for this work is the unit manufacturing process (UMP) information model defined in the recently revised ASTM E3012 (ASTM E3012, 2020). The purpose of the UMP model is to provide the necessary digital definitions to fully characterize models describing manufacturing processes. This includes all assumptions present in the model, i.e., free-text descriptions or mathematical definitions, the model's bounds of utility, and all model parameters formally characterized and codified[2]. The standard was specifically designed to handle environmental sustainability perspectives with one of the main goals to derive life cycle inventory (LCI) data in more consistent and robust ways (Bernstein et al., 2018b).

To demonstrate the generation of LCI data, several tools were developed to interface with the UMP conceptual model. In this paper, we leverage these tools to realize the proposed workflow. The UMP Builder (Bernstein et al., 2018a; Lechevalier and Bernstein, 2019) is a web-based tool that facilitates the recording and syntactic validation of UMP reference models. To "operationalize" the process models, Kulkarni et al. (2019) developed a plugin to "MOdel Composition and Analysis" (MOCA), a meta-modeling optimization tool, to accept UMP XML models. MOCA generates a python library with variable and expression descriptions of the UMP models and provides a link to simulation and optimization routines via OpenMDAO (Gray et al., 2010). Linking the UMP concept with Life Cycle Assessment (LCA) practice, Bernstein et al. (2019) demonstrated the integration of MOCA-generated process models with Brightway2 (Mutel, 2017), an open Python-based LCA framework.

Here, we extend these works to facilitate sensitivity analyses of product attributes relative to environmental sustainability performance considerations. The current example UMP schema (Bernstein and Lechevalier, 2019) does not differentiate model attributes based on whether they relate to product or process information. Instead, we classify model attributes based on their bounds and evaluation characteristics, e.g., whether a parameter is assumed to be fixed through the model evaluation or a control variable with specified bounds. Understanding the core differences between product-, design-, and process-anchored parameters should facilitate the advancement of the standard reference model.

Model-based design (MBD) describes a structured process for developing formal (often mathematically defined) design definitions to facilitate deeper understanding of how design characteristics relate to product life cycle considerations. MBD is traditionally leveraged in complex product systems, e.g., aircrafts and buildings. Defining design, manufacturing, inspection, and sustainment models is an expensive task. To lessen barriers to implementation, the International standards community has contributed information models to improve interoperability across these domains, i.e., design, production, inspection, and distribution (Lu et al., 2016). Introducing environmental sustainability considerations into these models has yet to be broadly standardized, but the current data representations already provide the necessary infrastructure for such perspectives (Brundage et al., 2018).

We present a case study that explores sensitivity of design characteristics relative to environmental sustainability-related evaluations using standard parametric modeling methods. Though there is limited work from the environmental sustainability perspective, there is plenty of MBD implementations exploring traditional performance indicators, e.g., cost, throughput, and quality (Simpson et al., 2008). Recent efforts focus on constructing design definitions that are robust to life cycle disruptions. Donndelinger and Ferguson (2017) characterized a design to better deal with anticipated downstream considerations through "slack" parameters. Kumar et al. (2008) developed a compressor blade design robust against manufacturing variations. Xue et al. (2008) leverage the Taguchi method to understand design attribute sensitivity to anticipated change. Though there are more examples of research projects, business methods, e.g., automated change requests, remain challenging in practice partly due to their lack of conformance to standard data representations, architectures, and interfaces (Hedberg et al., 2017).

CAD and computer-aided manufacturing (CAM) software offer great potential for developing workflows to explore relationships across a product's life cycle through open application programming interfaces (APIs). Chen et al. (2017) demonstrated the use of Siemens NX platform to relate LCA workflows to CAD-generated information. Similar efforts have been developed to interface with CAM intelligence. Gaha et al. (2016) manually generated possible manufacturing scenarios from each part feature within a CAD software to evaluate environmental performance during the design process. Russo and Rizzi (2014) developed the Eco-OptiCAD tool consisting of their own "standard" manufacturing process models relating CAD-based part features to environmental assessments. Tao et al. (2018) leverage a commercial system integration tool to relate product features with attributes within an LCA software to optimize products for environmental performance. Yet, such solutions are platform-specific and do not provide a strong standards angle for broad dissemination. In many cases, once information is retrieved from CAD/CAM systems, one-off prototypes are developed to perform problem-specific calculations to generate LCI data. The goal of our work is to construct a standards-based workflow that offers directions for platform-agnostic integration. Playing central roles, the UMP model (Bernstein and Lechevalier, 2019) and the tools built around it offer standard interfaces for LCI calculations.

3. Methodology

The overall methodology of the proposed workflow is illustrated in Fig. 1. Steps in this process are discussed below.

[1] https://www.solidworks.com/sustainability/sustainability-software.htm .

[2] Refer to the reference documentation (Bernstein and Lechevalier, 2019) to learn about the UMP model.

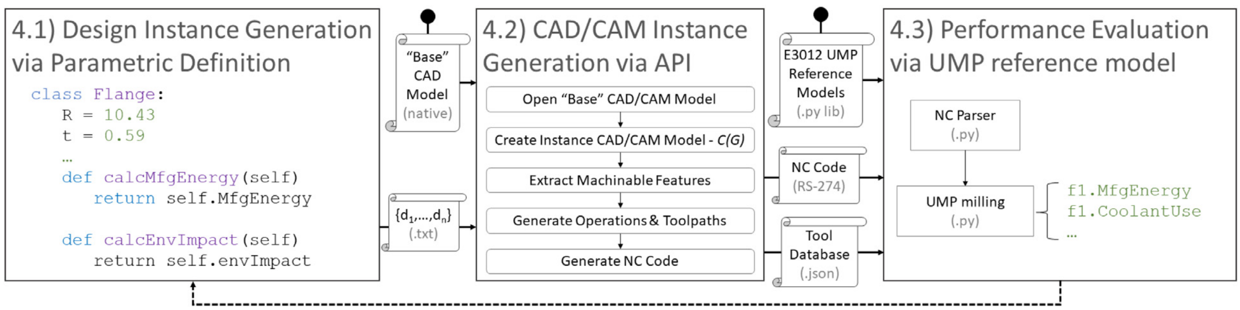

Fig. 1. Schematic describing the inputs and outputs of steps in the proposed workflow with exemplar methods called out in the workflow functions.

3.1. Formulating parametric CAD model and data structure

First, a parametric design model of the part is generated which consists of (i) a parameterized CAD "base" model and (ii) an object-oriented description of design variables and computed geometric and physical parameters, i.e., $\{d_i, ..., d_n\}$. The CAD model is parameterized based on a set of N independent driving geometric dimensions $G = \{g_i : 1 \leq i \leq N \wedge N \geq 1\}$. These dimensions, the driven geometric dimensions, and the geometric constraints between model elements are chosen such that they convey underlying design intent. The driving dimensions G cam ne instantiated to generate a valid CAD model $C(G)$ that is representative of a physically realizable mechanical part (see step 4.2).

The object-oriented description of the part includes a set of K independent design parameters $D = \{d_i : 1 \leq i \leq K \wedge K \geq 1\}$ that relate to part geometry ($G \subset D$) and metrics for part performance P. Instantiating a set of design parameters D produces a design model $M(D)$ with a corresponding CAD model $C(G)$. The model M also contains a description of constraints L on design requirements, e.g., required torque transmission for a coupling and moment of inertia for a flywheel, and physical constraints, e.g., limits of physical dimensions, yield strength of material. Thus, for a set of design parameters D, the validity of the model $M(D)$ can be checked based on their satisfying L.

3.2. Generating NC code for the manufacturing process

The CAD model $C(G)$ is generated within a commercial parametric CAD/CAM application. A model representing the initial stock model is generated by offsetting the minimum bounding box of the component by a predefined allowance. This is common practice to allow for variation in incoming raw material. The work coordinate systems used to define the location and orientation of the component within the machine tool for the two setups are then defined based on the CAD geometries.

Machining operations are determined by automatically extracting machinable features from the generated CAD geometry based on the defined machine and setup condition. Note that automatic feature extraction for CAD/CAM represents a rich area of research (Gao et al., 2004; Henderson and Anderson, 1984; Perng et al., 1990) but its implementation is not trivial as described later in the paper. The required tools for these operations are automatically selected from a predefined tool catalog, first by selecting the appropriate type of tool, e.g., a face mill for facing, an end mill for pockets, and a drill for holes, then choosing the appropriate tool size. In machining, it is preferred to use the largest tool possible to complete an operation, as larger tools provide a higher material removal rate (MRR) for a given set of machining conditions. For holes, a drill is chosen with a matching diameter. For internal pockets, an end mill is chosen which is smaller or equal to the minimum feature size, e.g., an internal corner radius. For open pockets, large tool sizes are chosen as they are not constrained by a minimum feature size.

Toolpaths are then created for each operation based on the operation type and defined manufacturing parameters. These parameters include cutting speed, chip load per tooth, axial tool engagement (depth of cut), and radial tool engagement (stepover). These parameters can vary between the specific machining operation type, the material to be machined, the cutting tool used, and the machine tool used in the process. NC code for the created toolpaths is then generated via a post-processor.

3.3. Evaluating performance indicators from the NC code

Once the NC code is obtained from the CAD/CAM application, we relate the instance data to the appropriate UMP reference model. Via MOCA, we generate a library of Python code by parsing through a E3012 validated model (Kulkarni et al., 2019). In the case of machining, we consider each NC code line as an individual machining scenario taking into account whether the machine is in rapid-traverse or active-cutting modes. Based on NC code standards (EIA, 1979), we developed a parser that evaluates each cut based on a previously constructed UMP model (Bernstein et al., 2019). These evaluations account for all necessary inputs into the process LCI. For more information, refer to the developed mapping method between E3012 and EcoSpold information models (Bernstein et al., 2019). The interaction of the two models using this mapping method enables selection of potential LCI models based on the corresponding UMP model. Brightway2 coupled with a commercial LCI activity database is used to compute environmental impacts.

For each design, we can access various performance indicators depending on the nature of the search. For example, for a machined flywheel, we can get simulated LCA results of the design-, setup-, and machine-specific process along with more traditional performance objectives, e.g., maximum Von Mises stresses computed using the input design parameters.

Our workflow supports cradle-to-gate LCA, while taking into account contributions from material and energy flows, i.e., input material, output waste, and recycled material. Although any LCA method can be used given that the incorporated databases support it, we use the ReCiPe method (Goedkoop et al., 2009), which helps translate various emissions and resource extractions into a limited number of eco-impact scores through characterization factors. In our case, we equally weight the final scores to report a single value; however, in practice, evaluating alternatives by considering scores separately is often more telling.

4. Case study

The proposed workflow enables automated evaluation of the performance indicators over an interval of design parameters. Therefore, the computed performance indicators can be used to

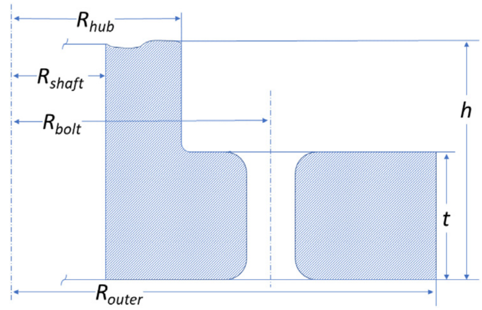

Fig. 2. Cross-section for parametric design of straight flanges (Blake, 1989)

drive iterative analyses commonly performed in the design stage, e.g., design optimization, sensitivity analyses, and trade-space exploration. We demonstrate the application of the workflow to one such case, determining the influence of design parameters on the cradle-to-gate environmental impact of a straight flange coupling design. For assessing the environmental impact of the flange coupling, we consider the amounts of (i) aluminum used for the stock material, (ii) mineral oil for machining, (iii) water consumed during machining, (iv) electricity consumed, (v) aluminum recycled, and (vi) oil recycled.

4.1. Design problem description

The parametric design model for the straight flange coupling was implemented as shown in Fig. 2. For more detailed information regarding the parameterization, please refer to the referenced dissertation (Qureshi, 2011). The objective of this case study is to identify the sensitivity of the design parameters to a computed cradle-to-gate environmental impact indicator. To this end, we selected four design parameters of the straight flange coupling. Below, we call out their nomenclature, with a brief description and value ranges studied. Values are presented in millimeters.

- R_{hub} – [30,90] – radius of the inner hub
- R_{outer} – [35,130] – radius of the flange assembly
- h – [20,30] – height of the flange part
- t – [1.5,20] – thickness of flange coupling

Design parameters that were fixed throughout our study include the bolt diameter ($D_{bolt} = 3mm$), the shaft diameter ($R_{shaft} = 25mm$), and the number of bolts ($N_{bolts} = 5$). To ensure the design's manufacturability, the following constraints were defined for generating each design alternative.

$$1.5t - h + 1 \geq 0 \tag{1}$$

$$R_{hub} + 0.5 - R_{outer} \geq 0 \tag{2}$$

$$R_{shaft} + 0.5 - R_{hub} \geq 0 \tag{3}$$

$$2R_{hub} - 2R_{bolt} + 1 + D_{bolt}/2 \geq 0 \tag{4}$$

$$2R_{bolt} + D_{bolt}/2 + 1 - 2R_{outer} \geq 0 \tag{5}$$

4.2. CAM considerations

The manufacturing process for the straight flange design implemented in this case study required two setups, as the straight flange component needed to be finished on all sides. In setup one, the component was face machined and all holes were drilled. In setup two, the other face and center boss of the component were machined. The required tools for these operations, e.g., the appropriate drills size for a hole, were automatically selected from a predefined tool catalog. This tool catalog contained a full range of drill bits in 0.5 mm increments, a range of endmills from 1 mm to 25 mm and small selection of facemills.

Once the tool has been selected for an operation, the machining parameters were assigned. The material used in this study was Aluminum. Therefore, a machining speed V_c was chosen based on the manufacturing database (approx. 250 m/min). This cutting speed determines the rotational speed of the cutting tool $N = (1000V_c)/d$. Feed velocity of the tool V_f is then calculated as $V_f = s_z N_t N$, where s_z represents the defined feed per tool and N_t represents the number of teeth on the cutter. The axial a_p and radial a_e depth of cut were defined conservatively as percentages of the tool diameter; $a_p = 0.2d,\ a_e = 0.1d$.

4.3. Sensitivity analysis of design parameters

We conduct a screening study (Iooss and Lemaître, 2015) to identify design parameters that significantly influence the resulting environmental impact. We adopt the method proposed by Morris (1991) for computing elementary effects. It classifies input variables (e.g., design parameters) into three categories, (i) design parameters with negligible effects, (ii) design parameters with significant linear effects and without interactions, and (iii) design parameters with significant non-linear effects and/or interaction effects (Iooss and Lemaître, 2015) based on the absolute mean and standard deviation of the elementary effects. Thus, results from these analyses can guide further exploration of specific design parameters and consequently guide generation of alternatives. The overall process for the screening analysis is shown in Algorithm 1 (A1) and is elaborated below. Given a nominal design D_{nom}, we performed a screening study in the neighborhood of the nominal design D_{limits}; $D_{limits} = D_{nom} \pm \omega$. The value of ω is set by the engineer performing the study. First, the study space (D_{limits}) is discretized into l levels as described in A1, line 2. Next, the elementary effect of each design parameter d_i on the set of performance parameters P is estimated for R random values of D as shown in A1, line 6. This is used to compute the mean absolute value (A1, line 8) and the standard deviation of the elementary effect (A1, line 9). A1 plans for independent random sampling and requires $2KR$ runs of the computational model.

Results of the screening study were further validated through a linear regression analysis that estimated the cradle-to-gate indicator using design parameters with significant elementary effects. Details about the fitted model are presented in Section 5.

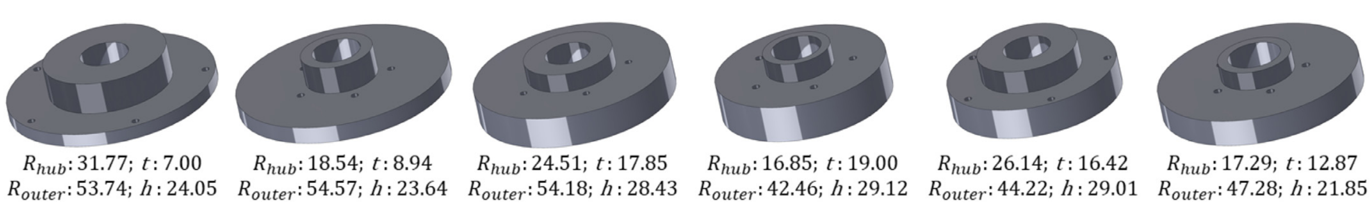

Fig. 3. Sample of the generated design alternatives evaluated throughout the design screening study. Design attributes are listed in millimeters.

Algorithm 1 Screening study for significant design parameters

function SCREENINGCALC(a, l, K, R, D_{limits}, M, C)
  $\delta D \leftarrow \dfrac{a}{l-1}$; $a, l \in \mathbb{Z}^+$
  ▷ l is number of levels of discretization of D_{limits}
  for i from 1 to K **do**
    for r from 1 to R **do**
      $D^r = random(D)$; $D \in D_{limits}$
      $E_i^r = \dfrac{gen(D^r + \delta D * u_i, M, C) - gen(D^r, M, C)}{\delta D}$
  ▷ u_i is a vector of canonical base
    end for
    $\mu_i^+ = \frac{1}{R}\sum_{r=1}^{R} |E_i^r|$
  ▷ compute mean absolute value of elementary effects
    $\sigma_i = \sqrt{\frac{1}{R}\sum_{r=1}^{R}\left(E_i^r - \frac{1}{R}\sum_{r=1}^{R} E_i^r\right)^2}$
  ▷ compute standard deviation of elementary effects
    $\mu^+ = \mu^+ \cup \mu_i^+$
    $\sigma = \sigma \cup \sigma_i$
  end for
  return μ^+, σ
end function

function GEN(D, M, C)
  instantiate $M(D)$, $C(G)$
  ▷ M is the design model, C is the CAD model, and $G \subset D$
  check validity of $M(D)$, $C(G)$
  ▷ verify L is satisfied & $C(G)$ is valid.
  $NC \leftarrow \{M(D), T\}$
  ▷ generate NC code for milling operations based on $M(D)$ & machine specifications T
  $P \leftarrow \{M(D), NC, EI\}$
  ▷ define eco-indicator P, based on $M(D)$, NC, & LCI database EI
  return P
  ▷ calculate and return P; the set of part performance metrics
end function

Table 1
Absolute means (μ^+) and standard deviations (σ) for elementary effects of parameters. Each μ^+ is greater than its estimated standard error ($\sigma/\sqrt{R}$).

	R_{hub}	h	t	R_{outer}
μ^+	8.3755	6.774	0.2414	8.3433
σ	1.8306	2.9157	0.4738	11.5984

4.4. Study setup

Simulations were performed on a desktop computer with an Intel Xeon E2186G @ 3.80 GHz processor. The object-oriented model of the straight flange coupling was implemented in the Python programming language and the parametric model was generated using SolidWorks®. CAMWorks® was used for generating the NC code that was fed into the UMP reference model. The following values of constants were used in the sensitivity analysis algorithm to compute elementary effects: $a = 1$; $l = 10$; $R = 100$; $K = 4$. The values of D_{limits} for the design parameters are detailed in Section 4.1. The values for a and l were set by the authors based on the design problem. The number of replications R was set by progressively increasing the number of replications to the point where we noticed insignificant deviation in the values for the computed elementary effects (Ruano et al., 2011).

5. Results

Fig. 3 illustrates six design alternatives generated during the screening study. A total of ($2KR = 800$) such alternatives were generated which resulted in a approximate total run time of 225 minutes. The absolute means and standard deviations (μ^+, σ) of the elementary effects for the four design parameters are shown in Table 1. We found the thickness of the flange (t) has low values of both μ^+ and σ. Therefore, variations in t in the neighborhood of D_{limits} does not have a significant influence on the computed cradle-to-gate indicator. On the other hand, the three other design parameters (R_{hub}, h, and R_{outer}) had significantly high values for both μ^+ and σ. Therefore, we can conclude these variables have significant non-linear effects and/or interaction effects on the computed cradle-to-gate indicator. Eq. (6) details the model for the linear regression analysis performed to validate results from the screening study.

$$\begin{aligned} ecoimpact = {} & \beta_0 + \beta_1(R_{hub}) + \beta_2(h) + \beta_3(R_{outer}) + \\ & \beta_4(R_{hub}^2) + \beta_5(h^2) + \beta_6(R_{outer}^2) + \beta_7(R_{outer} * R_{hub}) + \\ & \beta_8(R_{outer} * h) + \beta_9(R_{hub} * h) \end{aligned} \quad (6)$$

We included second-degree terms for the three significant design parameters as they directly relate to the overall part volume. We also included all two-way interaction terms between the design parameters as we anticipated such interactions could significantly change the process plan and consequently influence the computed indicator. Results from the ordinary least squares regression analysis shows the model was significantly different from a constant model ($F_{7,790} = 841.2$; $p < 0.001$). The parameter estimates for the model terms are illustrated in Tbl. 2. Results show the linear terms for all three design parameters (R_{hub}, h, R_{outer}) were significant predictors for *ecoimpact* at a significance level of 0.01. The terms are positively correlated to *ecoimpact* (evidenced by the positive values for their estimates), which is intuitive; increasing the scale of the mechanical part, increases the impact in both material extraction and machining. Only the second-order terms R_{hub}^2 and R_{outer}^2 were significant predictors for *ecoimpact*. This is supported by the fact that the part volume is directly proportional to R_{hub}^2 and R_{outer}^2 while it is linearly related to h. A surprising result from our analysis is R_{outer}^2 was inversely related to *ecoimpact*. This can be partly explained by the fact that there is an increase in

Table 2
Estimated coefficients along with 95% confidence intervals for the linear regression model described in Eq. (6).

Term	Estimate	Std error	t Ratio	Prob>|t|	Lower 95%	Upper 95%
Intercept	−0.253	0.034	−7.47	<.0001	−0.319	−0.186
R_{hub}	7.740	0.229	33.860	<.0001	7.292	8.189
h	7.351	0.965	7.620	<.0001	5.457	9.244
R_{outer}	8.540	0.191	44.770	<.0001	8.165	8.914
(R_{hub}-0.0499)*(R_{hub}-0.0499)	60.697	12.559	4.830	<.0001	36.043	85.350
(h-0.0256)*(h-0.0256)	−175.451	351.547	−0.50	0.618	−865.527	514.626
(R_{outer}-0.109)*(R_{outer}-0.109)	−50.201	9.057	−5.54	<.0001	−67.979	−32.423
(R_{outer}-0.109)*(h-0.0256)	−77.103	60.712	−1.27	0.205	−196.278	42.072
(R_{outer}-0.109)*(R_{hub}-0.0499)	17.362	15.360	1.130	0.259	−12.789	47.513
(h-0.0256)*(R_{hub}-0.0499)	207.651	67.997	3.050	0.0023	74.174	341.128

environmental credit from recycling of machining scrap and mineral oil with an increase in R^2_{outer}. Results also show that $h^{*}R_{hub}$ was the only significant interaction term in the model, which can be explained by the fact that these design parameters directly influence the generated toolpaths. However, a deeper analysis of the underlying LCI model and design parameters is required to fully explain these findings.

6. Conclusions

Some of the most significant limitations lie within the quality of the CAM automation and simulation. We heavily rely on the automated identification of machining operations, tool selection, and toolpath generation, provided by the CAM software's capabilities. In practice, it is unlikely that operators would trust the quality of automated process plans without rigorous validation to avoid machining problems, e.g., collisions. That being said, we interact with the CAM tool's API to eliminate redundant operations and other issues identified through this exercise. Coupled with the NC code generation, the NC parser that was developed in-house also is admittedly not at the performance level of commercial simulation tools, such as Vericut[3]. To stay grounded, we compared our results against Vericut by randomly selecting a few designs. We found that the material removal, total machining time, and total distance traveled estimations were comparable, i.e., in the same orders of magnitude. Incorporating more advanced simulation tools would obviously improve the accuracy of the performance evaluations but would increase the overall computational time of the design screening process. Such trade-offs should be explored in future research.

Other limitations relate to the complexities of the part and models. In our case, we study a fairly simple design in which only four attributes are explored. We also do not consider effects of hole drilling in our simulation, since we only parse NC codes related to milling operations. Currently developing a drilling UMP reference model, we plan to incorporate multiple UMP reference models into our pipeline. Studying these effects will be a novel step forward understanding detailed environmental impacts of machining setups and operations. Moreover, though our motivation is to enable consideration of multiple downstream stages, including use and sustainment, at design, we only focus on manufacturing-driven impacts. To encode other information's effects within the UMP concept, we plan to partner with on-going standards efforts in the systems engineering community to embed promising representations into our pipeline.

In summary, we described a standards-based workflow that provides a new way to quantify the environmental impact of manufacturing processes. Starting with a parametric model with N independent design parameters, a CAM stock is created by a minimum bounding block and machining operations are automatically created by extracting geometry. Using predefined processes, NC code is generated and sent to a UMP reference model where NC code lines are parsed, creating inputs for the process LCI. Brightway2 is coupled with an LCI database to compute the environmental impacts. A case study on a rigid flange illustrated the ability to identity design parameters with the largest effect on the environmental impact. These quantitative values take into account geometric complexity which is currently not considered by other commonly used software.

Disclaimer

CRediT authorship contribution statement

William Z. Bernstein: Software, Conceptualization, Methodology, Formal analysis, Investigation, Writing - original draft, Supervision, Project administration. **Melissa Tensa:** Methodology, Writing - original draft. **Maxwell Praniewicz:** Methodology, Validation, Writing - original draft. **Soonjo Kwon:** Software. **Devarajan Ramanujan:** Software, Conceptualization, Validation, Formal analysis, Investigation, Writing - original draft.

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[3] More information can be found at https://www.cgtech.com/.

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