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Quantifying Life Cycle Inventories for Machining Processes at Detailed Design

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Abstract

This paper quantifies machining process inventories based on commonly used techniques in various stages of the detailed design process. We investigate variabilities in process inventories between these techniques and their relation to manufacturing process parameters, which are required for generating machine-level instructions. We also benchmark these process inventory modeling techniques against experimental measurements. We then showcase potential issues of using available process models without properly accounting for product and process differences. Our results caution practitioners against basing their environmental analyses on data collected prior to detailed process planning. We conclude that accurate quantification of machining process inventories requires combining accurate simulation-based models with data-driven estimates for model parameters.

Keywords: Sustainable manufacturing; Unit manufacturing process; ASTM E3012-20; Process modeling

1. Introduction

Product design activities fix a significant portion of the lifecycle environmental impact of products [3, 8]. Design processes also heavily influence environmental impacts related to manufacturing, as detailed design fix part characteristics (i.e., materials, geometry) and manufacturing process definitions. Consequently, quantifying manufacturing-phase impacts at the detailed design stage can help designers and engineers to proactively optimize part characteristics and process parameters from an environmental sustainability perspective.

However, estimating manufacturing-phase impacts during the design stage is challenging due to limited availability of downstream lifecycle information [15]. Such information gaps can lead to uncertainties for evaluating the environmental benefits of design changes [9]. Our previous work began to address these challenges. Specifically, we developed a standards-based workflow [6] that aimed to quantify environmental performance indicators at the detailed design stage. Our workflow links parametric computer-aided design (CAD) models to unit process lifecycle inventories (LCIs). This paper extends our previous work by estimating variabilities in process LCIs resulting from incomplete knowledge of design and manufacturing process parameters. Specifically, we leverage a unit manufacturing process (UMP) model for machining processes. We then compare the process LCIs for machining a reference test part via a computer-aided manufacturing (CAM) software-based simulation against experimentally measured values for energy consumption. Our results shed light on the magnitude of uncertainties for estimating process inventories at various stages of the detailed design process.

2. Background

The basis of this work is the UMP modeling technique defined in ASTM E3012-20 [1]. UMP instance models provide the necessary digital definitions to fully characterize manufacturing processes. These definitions include assumptions present in the defined model, i.e., text-based descriptions or mathematical formulations, the process model's bounds of utility, and all model parameters formally characterized and codified[1]. ASTM

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[1] Refer to the reference documentation [4] to learn about the UMP model.

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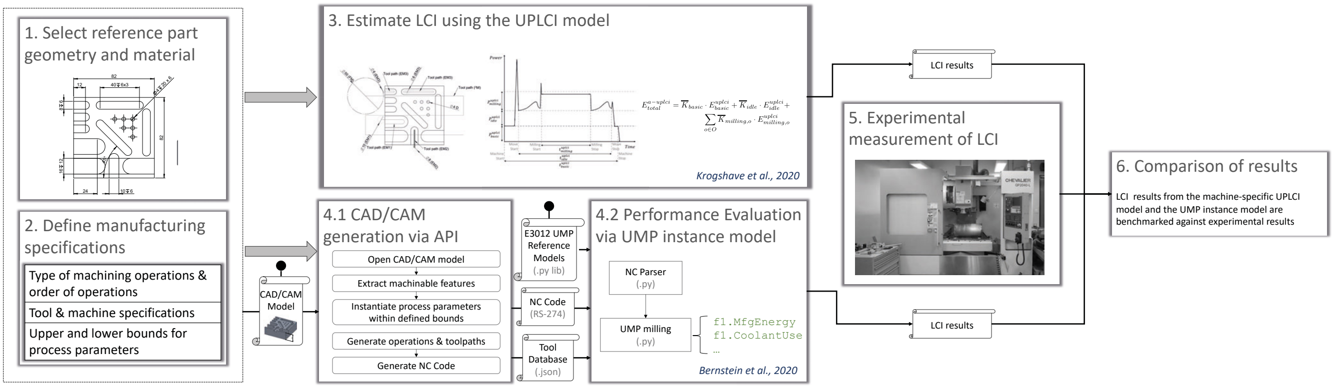

Fig. 1. Overview of the methodology for estimating process LCIs. Results from the UPLCI model constructed prior to estimating a detailed machining plan, was compared with results from the UMP instance model constructed with CAD/CAM data, and experimental results.

E3012-20 was designed to handle environmental sustainability perspectives. The standard aims to drive manufacturing-based LCI data in more consistent and robust ways [7].

Estimating resource consumption in manufacturing processes during detailed design and process planning are important steps for reducing manufacturing-related impacts [8, 10]. The $CO_2PE!$ unit process lifecycle inventory (UPLCI) framework [17] was among the first research efforts that focused on defining a consistent methodology for parametric estimation of LCIs for UMPs based on their process parameters. CO2PE is an LCA-oriented methodology in which process LCI is collected in two different levels of detail, a screening approach and an in-depth approach. The UPLCI framework details a formalized process for collecting, documenting, and providing LCIs for various UMPs. Under the UPLCI framework, researchers have developed UMP models for 31 unit processes, including material reducing processes such as milling, drilling, boring, turning, and grinding [16].

This paper specifically focuses on the UPLCI milling model, originally defined in Kalla et al. [13]. The UPLCI milling model uses a combination of physics-based first principle estimates and empirical data measurements applicable to a variety of materials and machine tools. However, if a specific machine tool is specified, the assumptions made in the UPLCI milling model can lead to significant errors in estimating milling energy consumption [14]. Krogshave et al. [14] discuss a method for constructing a machine-specific UPLCI model that accounts for uncertainties in machine, tool, and workpiece specifications.

3. Methodology

Fig. 1 overviews our methodology. We provide details for each step below in the forthcoming subsections.

1. **Defining a reference test part:** We establish parameters for the test run(s), including information about design and process plans. Describing the setup allows others to replicate or adapt the setup for analyzing other installations.
2. **Defining specifications for the process and machine tool(s):** We define all specifications of machine tool(s) to produce the part. We also record information on (i) the individual operations to produce the parts, (ii) tools used for machining the part's features, and (iii) the bounds for the process parameters for each feature.
3. **Estimating LCI via UPLCI model:** We estimate the LCI for producing parts using the UPLCI model defined in Krogshave et al. [14]. The UPLCI model is constructed before creating a detailed machining plan and uses approximate data on tool paths and process parameters. We then estimate machine-specific adjustment factors for the UPLCI model that quantify the accuracy of the LCI results for milling, idle, and basic energy consumption.
4. **Predicting LCI results through UMP reference model** A detailed simulation of the manufacturing process plans via CAD/CAM software estimates LCI for producing the part. As shown in Fig. 1, we first instantiate a UMP milling model via CAM data and the E3012 reference model. Next, LCI results are used to estimate machine-specific adjustment factors for the various energy consumption modes of the machine tool.
5. **Experimentally measuring LCI:** We build the reference part using the process parameters bounds and the machine tool identified in Step 2. We then experimentally measure the LCI for building the reference part.
6. **Comparing the results:** We benchmark the results from the UPLCI model and the UMP instance model against experimental results. We interpret these comparisons to gain insight on the variabilities in the LCI resulting from the lack of accurate product and process information.

3.1. Defining a reference test part

Figure 2 shows the reference test part used for developing the UPLCI model. We leverage a reference test part used in previous studies [2, 11], which adapted the test part[2] from a Japanese Standards Association (JSA) standard [12]. Part features are machined in the following order: face milling (F1),

[2] The geometry for the reference test part used in our paper can be downloaded from this link: `https://tinyurl.com/jsapart`.

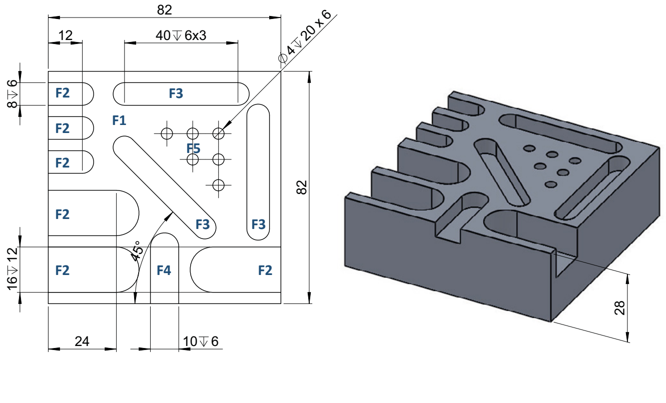

Fig. 2. Reference test part used. Adapted from Behrendt et al. [2].

three large grooves and three small grooves (F2), three pockets oriented along the X-axis, Y-axis, and 45° (F3), trochoidal groove (F4), and six holes (F5).

We excluded the drilled features (F5) from our study to restrict the focus to milling operations. Results from machining the trochoidal groove (F4) are not presented as it was challenging to assess the time for active cutting in our experimental runs. We machined the reference test part using Aluminum 6082 assuming a specific cutting energy (SCE) of $0.7 \frac{J}{mm^3}$ [13].

3.2. Defining specifications for the process and machine tool

We machined the reference test part on a Chevalier QP2040-L 3-axis vertical milling machine tool[3]. The machine included a control panel, an automatic tool changer, and a cutting fluid pump. The machine tool specifications defined to compute results using the UPLCI model [13] included the following.

- We estimated the basic power consumption as 3.75 kW. We based this estimate on the assumption that the basic power consumption was 25% of the maximum power consumption of the machine tool (15 kW).
- We estimated the idle power consumption as 9.67 kW. We determined this value by summing the following:
  - Power demand from X-,Y- & Z- axis motors = $\frac{1}{3} \cdot (2.98 + 2.98 + 4.03) = 3.33$ kW
  - 50% of rated power consumption from the spindle motor = $\frac{1}{3} \cdot 11.19 = 3.73$ kW
  - Rated power demand from fluid pump = 0.75 kW

Table 1 details the tools used for machining each feature on the reference test part. As shown, face milling operations were performed by a 50 mm face mill with 5 inserts. End-milling operations were performed by three different end mills (6, 8 and 10 mm) with 4 inserts.

After consulting with our workshop's technician, we chose process specifications on the Chevalier QP2040-L. Table 2 details the bounds for the process parameters based on the machine tool capabilities and the part requirements. We employ

[3] Machine specifications are foudn at https://tinyurl.com/chevalierQP2040-L.

Table 1. Specifications for the tools used for machining the reference test parts.

Tool		Diameter [mm]	Teeth
Face mill	FM	50	5
End mill	EM1	10	4
	EM2	8	4
	EM3	6	4
	EM4	4	4

a safety distance of 1 mm and a rapid feed rate of 15000 $\frac{mm}{min}$. We clamped the part with a stationary parallel holding vice. We estimated the time for loading and unloading the part as 19.6 seconds [13]. We assumed that all workpieces were manually handled. The loading process included opening/closing the machine door and clamping the workpiece. Unloading included opening the door, cleaning, and unclamping the workpiece.

Experience UPLCI practitioners might use more accurate power estimates. However, we use specifications from Kalla et al. [13] to study the impact of generic estimates.

3.3. Estimating LCI via UPLCI model

Our previous work [14] forms the basis for estimating the LCI for the reference test part. We developed a machine-specific UPLCI model that improved the prediction accuracy of the original UPLCI model. In the current work, we adopt a similar procedure for estimating the energy consumption. We model machine-specific energy consumption as given in Eq. 1.

$$E_{total}^{m-uplci} = \overline{K}_{basic} \cdot E_{basic}^{uplci} + \overline{K}_{idle} \cdot E_{idle}^{uplci} + \sum_{o \in O} \overline{K}_{milling,o} \cdot E_{milling,o}^{uplci} \tag{1}$$

Eq. 2 estimates the mean value for the adjustment factors in Eq. 1. These factors quantify the accuracy of the model in estimating energy consumption for the milling, idle, and basic modes.

$$\overline{K}_* = \frac{\sum_{i=1}^{N} \frac{E_{*,i}^{real}}{E_{*,i}^{uplci}}}{N} \tag{2}$$

$E_{total}^{m-uplci}$ represents the total energy consumption estimated using the machine-specific UPLCI model. E_*^{uplci} represents the energy consumption in mode "$*$" estimated using the UPLCI model- $E_{milling,o}^{uplci}$ represents the energy consumption in milling mode for operation o estimated using the UPLCI model. N is the number of experimental runs. $E_{*,i}^{real}$ is the measured energy consumption in mode $*$ for experimental run i. $\overline{K}_*$ refers to the mean value of machine-specific adjustment factor for energy consumption in mode $*$. $\overline{K}_{milling,o}$ represents the mean value of machine-specific adjustment factor for energy consumption in

Table 2. Process parameters used for milling various features in the reference test part on the Chevalier QP2040-L milling machine. The tool listed in parenthesis for a each operation is specified in Tbl. 1. The values shown for the feed rate and spindle speed represent the bounds (Low–High) for these parameters.

	Face milling	Groove	Pocket	Trochoidal milling
Depth of cut [mm]	1,2,3 (FM)	6 (EM3), 10 (EM1)	6 (EM3)	6 (EM2)
Feed Rate [mm/min]	1000–1210 (FM)	300–605 (EM3), 600–1089 (EM1)	300–363 (EM3)	500–605 (EM2)
Spindle speed [RPM]	2200–2420 (FM)	3500–5500 (EM3), 3500–5000 (EM1)	5000–5500 (EM3)	4000–4400 (EM2)

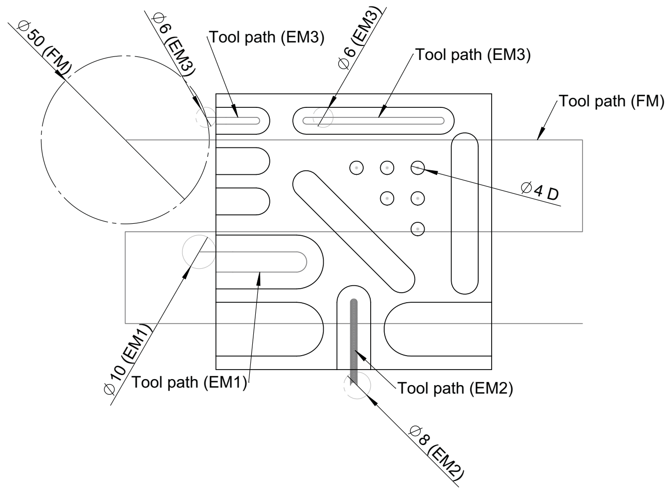

Fig. 3. Routing plan for the reference test part.

milling mode for operation o. We estimate the adjustment factors for the UPLCI model based on approximate process plans, i.e., without including information on specific tool paths.

Figure 3 shows the milling routing for the reference test part used in estimating energy consumption for the UPLCI model. We estimated the length of cut prior to setting up the numerical control (NC) code based on feature geometry and available tools (Tbl. 1). We calculated the length of cut per feature as the sum of the linear length of cut, the extended length of cut [13], and the circular length of cut. The overall length of cut (excluding trochoidal milling) is 2114 mm. We calculated total aircut distance between features as 808 mm. We found that overtravel distance from the assumed safety distance and accounts for 603 mm for all operations. We estimate the distance per tool change as 1088 mm, or 4353 mm for all four tool changes.

3.4. Predicting LCI results through UMP instance model

Our previous work [6] provides a workflow for generating LCI data from NC code through a UMP instance model. In this work, we use the same workflow to estimate LCI outputs. The workflow includes an NC code parser that computes the volume removal rate, active cutting time, rapid travel time, and other machining metrics per each instructional line. In doing so, we estimate machining times assuming ideal conditions, e.g., without considering operator overrides and motor-based uncertainties. We expect that the time evaluations (both from rapid and cutting movements) will underestimate real-world machining.

For predicting energy consumption, we used the same estimates as described in Sec. 3.2, including basic power (3.75 kW), loading/unloading time (19.6 sec), tooling information (Tbl. 1), and rapid feed rate (15000 $\frac{mm}{min}$). We isolate individual machining features by segmenting the NC code. We then evaluate separate times and energy consumption per segment.

To compare against the experimental results [14], we produced variations of the NC code for each scenario in Tbl. 2. For LCI results from the UMP instance model, the mean values for the adjustment factors were also estimated using Eq. 2, wherein $E^{uplci}_{*,i}$ is replaced by the corresponding energy consumption values estimated from a UMP simulation.

3.5. Experimentally measuring energy consumption

We measured the energy consumed for machining the test part to provide a baseline for the two estimation approaches. We used an SCT013-000 hall effect current sensor to measure apparent power consumption at the main supply line. As the machine tool uses 3-phase AC power, apparent power consumption was computed as the product of the root mean square value of the measured current (400 samples per cycle) and a fixed supply voltage of 230 V. The current measurement was made on a single phase and the system was assumed to be well balanced. The sensor has a measurement range of 0-100 A and an output range of 0-50 mA with a non-linearity of +/- 3 %. The sensor's measurement uncertainty was ± 8.5 % in the measurement range of 0-100 A[4]. An ADXL 345 3-axis accelerometer was attached to the bottom of the workpiece to identify the time periods during which the cutting tool contacted the workpiece. We used an Arduino Duo to process the sensor data and outputted them to a laptop computer. Krogshave et al. [14] provide more detail for this experimental procedure.

We machined 8 reference test parts (RP1-8) with varying process parameters detailed in Tbl. 2. We used 4 combinations of spindle speed and feed rates (low-low, high-high, low-high, and high-low). Thus, two pairs of parts (RP1&RP5, RP2&RP6...) were machined with identical process parameters.

3.6. Comparing machine-specific adjustment factors

We computed the machine-specific adjustment factors for the UPLCI model and the UMP instance model using the experimental measurements for the reference test part (see by Eq. 2). The resulting values provide insight into the uncertainties in using the above models to estimate LCI at various stages

[4] For Yhdc Current Transformer info, refer to https://tinyurl.com/yhdc100.

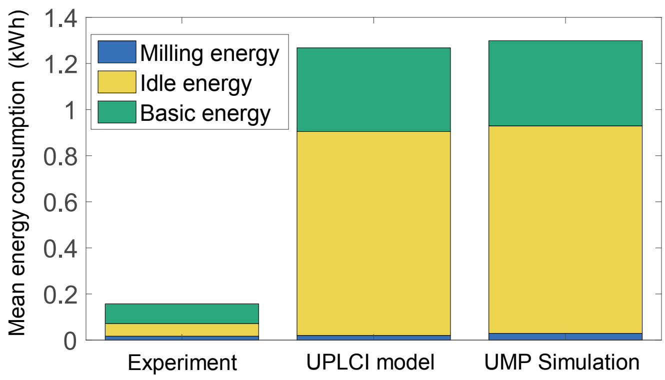

Fig. 4. Mean energy consumption for milling, idle, and basic modes for the experimental measurements, UPLCI model and the UMP simulation.

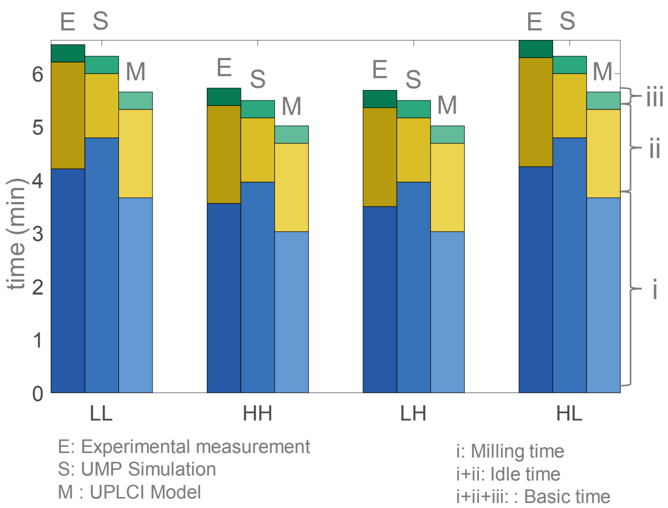

Fig. 5. Comparison of milling, idle, and basic times for the experimental measurements, UMP simulation, and the UPLCI model. Table 2 give the low (L) and high (H) values for spindle speeds and feed rates.

of the detailed design step. For example, a $\overline{K_*}$ value of 1 indicates that the estimations are identical to nominal values from experimental measurements. A $\overline{K_*}$ value less than 1 indicates that the model overestimated energy consumption for that specific mode. We also compared times in milling, idle, and basic modes estimated using the machine-specific UPLCI model and the UMP instance model against experimental results.

4. Results

Figure 4 shows the mean energy consumption for milling, idle, and basic energy from the experimental measurements, UPLCI model, and UMP simulation. Both the UPLCI model and the UMP simulation significantly overestimated idle and basic energy consumption. In both cases, the idle energy consumption was overestimated by 1500 % when compared to experimental measurements. Similarly, basic energy consumption was overestimated by more than 300 %. The UMP Simulation overestimated milling energy by 72 % and the UPLCI model underestimated the same by 18.54 %. Although both approaches estimated milling energy consumption more accurately, active cutting only accounted for 10.75 % of the total energy consumption for machining the reference test part.

To investigate the sources of these errors, we compared milling, idle, and basic times, as shown in Fig. 5. As shown, the total time for machining the reference test part (basic time) was underestimated by the UMP simulation and the UPLCI model for all combinations of process parameter variations. The average error in basic time (across all four cases) was 0.234 minutes and 0.81 minutes for the UMP simulation and the UPLCI model, respectively. The basic time was estimated as the sum of the idle time and a constant time of 19.6 seconds for loading/unloading the part and cleaning the machine. Therefore, the average error in estimating the idle time was the same as that for the basic time. On average, the UMP simulation overestimated the milling time by 0.497 minutes while the UPLCI model underestimated the same by 0.532 minutes.

Table 3. Mean values of adjustment factors for machining the reference test part on the Chevalier QP2040-L. The adjustment factors are computed using Eq. 2

Milling operation (o)	$\overline{K}^{UPLCI}_{milling,o}$	$\overline{K}^{UMP}_{milling,o}$
Face milling	1.01	0.52
Groove milling	0.633	1.289
Pocketing	0.912	0.324
Mode ($*$)	$\overline{K}^{UPLCI}_{*}$	$\overline{K}^{UMP}_{*}$
Idle	0.0623	0.622
Basic	0.2347	0.2307
Total	0.1211	0.1240

Table 3 details the mean value of the adjustment factors for the UMP simulation and the UPLCI model. Results show the UMP simulation overestimated energy consumption for face milling and pocketing, while it underestimated energy consumption for groove milling. In general, the UPLCI model was more accurate in estimating milling energy consumption than the UMP simulation. The two approaches have nearly similar values of adjustment factors for idle and basic modes. This indicates the greater accuracy of the UMP simulation in estimating idle and basic time as compared to the UPLCI model. However, it did not result in significantly better accuracy for energy estimation. The same trend is seen for total energy consumption.

5. Discussions

Results showed the UPLCI model significantly underestimated the time in basic and idle mode. This resulted from the facts that (i) the achieved feed rates in the experiment were lower than the set feed rates in the UPLCI model, and (ii) the model considerably simplified the tool path due to lack of information on routing features such as tool ramping and entry/exit operations for complex geometric features. The method for estimating idle and basic power consumption in the UPLCI model (see Section 3.2) resulted in these values being overestimated. The idle and basic power estimated according to the UPLCI model was 9.67 kW and 3.75 kW, respectively; experimental results showed these values to be 0.57 kW and 0.832 kW. The UMP instance model was more accurate than the UPLCI model in estimating idle and basic time. However, the increased accuracy in estimating these times was overshadowed by the fact that the values for idle and basic power consumption input into the model were identical to the UPLCI methodology. The adjustment factors computed for the UMP instance model in Tbl. 3 reflect this fact, as evidenced by being lower than the corresponding factors for the UPLCI model.

Table 3 indicates that the UPLCI model was more accurate than the UMP instance model for estimating milling energy consumption. On investigation, we found that the cutting length computed by the UMP simulation using the NC code included portions of the toolpath, e.g., ramps and tool re-positioning, that do not necessarily remove material. The UPLCI model classifies such operations under the idle mode. In our experiments, we used an 3-axis accelerometer (attached to the workpiece) in combination with the current sensor to separate cutting and non-cutting states. However, the NC parser used for the UMP simulation does not model contact between the workpiece and the tool. Our discussion points to the following.

- Discrepancies between experimental measurements, the UPLCI model, and the UMP reference model with UPLCI estimations, show that evaluating LCI data for manufacturing processes remain a significant hurdle.
- Improving the accuracy of estimating LCI data requires practitioners to combine simulation-based modeling with data-driven estimation from experiments.
  - For example, the UMP reference model predicts the total accumulated time of the process much more precisely compared with the UPLCI estimates.
  - Machine-specific data for idle and basic power consumption that are collected from experiments can significantly improve the estimation for idle and basic energy for the UMP reference model.
- For the above techniques to be implemented at scale, the following challenges need to be addressed.
  - ASTM E3012-20 has not yet been implemented at scale. Passing the right data to the appropriate model requires its own architecture.
  - Designers require tooling and process specifications early. This assumes the availability of historical data from the machine tools.

We will focus future research on improving LCI estimation for life cycle assessments (LCAs). In previous work [5, 6], we demonstrated how our CAD/CAM workflow can integrate with an open-source LCA tookits. Relating LCA results to machining and design features based on real machine instructions opens the door for improving the accuracy of sustainability evaluations for machining processes.

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