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A Systematic Framework for Quantifying Production System-Specific Challenges in Life Cycle Inventory Data Collection

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Abstract

Understanding the environmental impacts of production setups and process parameters is a necessity for process optimization and new process development within sustainable manufacturing. Previous research studies have focused on developing standard methodologies and frameworks for parametrically modelling the life cycle inventories of unit manufacturing processes. However, these approaches do not fully account for the challenges associated with implementing life cycle inventory models in real-world production setups. Therefore, the time- and cost-intensiveness associated with constructing such models limit their use for identifying sustainability-focused process improvements in complex, real-world production processes. To address the above challenges, this paper proposes a framework to identify process inventory data that have a significant influence on process resource consumption, taking into consideration the difficulties and variabilities in measuring these data. The overarching goal is to identify feasible process improvements from the perspective of process monitoring for sustainable manufacturing. The application of the proposed framework is presented using a case study on a real-world through-feed centerless grinding production process for rotor manufacturing. This study reveals grinding time is the most sensitive process parameter among the other time-related parameters. The manual nature of the process, lack of a data acquisition system, non-standardized sequence of operation, and inability to capture in-process measurements without disrupting real-time production significantly contributes to the difficulty and variability of measuring grinding time.

Keywords: Sustainable Manufacturing; Life Cycle Assessment; Process modelling;

1. Introduction

Environmental sustainability in the industrial sector is an important concern as manufacturing processes can have a significant ecological footprint. Thus, developing accurate methodologies and tools for quantifying impact assessment is imperative [10].

Metrics of the sustainability performance of manufacturing processes, such as energy consumption, material loss, waste and emissions, can only be detected and estimated if the data is reliable and available [11]. Therefore, numerous previous research addressed the issues with regards to data uncertainties required to perform accurate life cycle assessment (LCA) [5]. A few frameworks have been developed to quantify these challenges to analyze sustainability performance of manufacturing processes accurately [8, 12].

The recently developed unit process life cycle inventory (UPLCI) framework represents the data collection and analysis methodology, thus providing the more detailed life cycle inventory (LCI) of manufacturing processes. Thus, UPLCI models can only be applied and reused if there is access to reliable data. While UPLCI models have been developed for a wide range of manufacturing processes [13], there is a lack of prior research on applying (and adapting) them towards real-world production setups. Data availability and reliability issues and the lack of process knowledge common in production facilities pose a significant challenge in identifying sustainability-focused process improvements based on UPLCI models. To address the above research gaps, this paper proposes a framework for quantifying the *difficulty*- and *variability*-related challenges associated with measuring *critical* process parameters. Here, critical process parameters are defined as parameters that significantly influence the resulting energy and resource consumption of the

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process. The proposed framework is demonstrated using a case study on characterizing the difficulty and variability of critical time-related process parameters for an existing through-feed centerless grinding production setup for rotor production.

2. Background

Several researchers have applied the UPLCI methodology to model different manufacturing processes to create reusable energy and mass loss estimation tools. A recent study by Overcash et al. [13] identified 31 distinct UPLCI models that have been developed for a range of conventional manufacturing processes, while the number of such models for non-conventional manufacturing processes [16, 18] is steadily increasing. However, there are always some challenges and/or limitations associated with the development of such models that have been discussed in this section.

Raoufi et al. [15] created a UPLCI model focused on the energy consumption evaluation for metal injection moulding process. However, some of the assumptions have been indicated during the calculation of basic energy, such as, basic power of the moulding machine, ovens and furnaces, which may result in the variation of energy values for different production setups. Ramirez-Cedillo et al. [14] applied the UPLCI methodology to evaluate the energy consumption and material losses for the laser powder bed fusion process. The authors stated that the energy consumption of active actuators and the laser efficiency were not considered due to the unavailability of specialized equipment, which could be helpful to determine the exact amount of idle and active energy used during the process. Simon et al. [16] developed a reusable model for stereolithography 3D printing and examined material and energy flow during the process. Experiments were performed to validate the developed model, and the empirical results were found in agreement with the proposed model. However, the developed model did not include post-processing stages (e.g., part cleaning and curing), resulting in underestimating environmental impacts. Buis et al. [3] performed sequential hot forming processes (consisted of heating, performing and extrusion) to estimate the energy consumption. Waste generation and process emissions were not considered in this study due to the inaccessibility of data.

Concerning the grinding process, a reusable UPLCI model was created by Linke and Overcash [9]. Limitations found for constructing the model include neglecting tool change time and loss of cooling lubricant. Also, the model adopted specific grinding energy values from the previous research studies and used an estimation for idle time, which could impact the applicability of the model in the real-time production scenario. A sustainability study of the grinding process was performed by Filleti et al. [4] based on the UPLCI methodology and real-time operational data. Due to the unavailability of LCI data related to the grinding wheel composition as well as cutting fluid consumption and composition, these aspects could not be integrated into the model. Kalla et al. [6] developed a UPLCI model for milling processes. However, a significant difference between theoretically estimated and experimentally measured values for milling energy consumption was reported by Krogshave et al. [17]. Overestimation of the machine tool's basic and idle power consumption was observed as the primary source for these errors. This work was further extended by Boettjer et al. [2] who developed an adjusted UPLCI model for estimating the machine tool-specific energy consumption in milling operations while considering the uncertainties associated with specific cutting energy of workpiece material and the machine tool specifications. The authors found that factors not considered in the previous model, such as complex tool path, machine tool life, wear of both cutting tool and machine tool, led to underestimating milling time and overestimating power consumption. The recent study by Bernstein et al. [1] addressed the variabilities in the estimation of process LCIs that arose due to a lack of process knowledge with regards to design and manufacturing process parameters. They proposed a methodology for comparing estimated LCIs, throughout the process-specific UPLCI and UMP reference models and experimentally measured LCIs. The results showed significant deviation in LCIs estimation.

Based on the above studies, it can be concluded that unavailability of measurement equipment, data inaccessibility, and uncertainties in the manufacturing process (machine tool specifications, cutting tool specifications, production setup conditions, etc.) are significant challenges associated with the development of UPLCI models. These challenges must be avoided to depict more accurate values for the UPLCI models and to enable sustainability-focused improvements in the process. This can be possible by collecting detailed and real-time production data for the defined manufacturing processes.

3. Methodology

The following sections describe the outline of the proposed framework developed to identify the process inventory data that have a significant impact on the sustainability performance of manufacturing processes. Sec. 3.1 presents process for constructing the overall UMP model, Sec. 3.2 shows the steps for decomposing the overall UMP model. Sec. 3.3 describes the development of UPLCI model based on decomposed UMP model. Lastly, Sec. 3.4 shows the approach used to develop criteria for difficulty and variability assessment as well as criticality assessment (via sensitivity analysis).

3.1. Overall UMP Model

Knowledge about the key metrics of sustainability performance and process familiarity are important aspects for assessing the environmental impacts of manufacturing processes. To create an overview of any manufacturing process, the unit operation model can be applied, thus providing information about all the process's inputs and outputs. Figure 1(a) presents the overall material and energy inputs and outputs for general manufacturing processes. However, this overview does not provide information about system limitations. Further decomposition of the UMP model characterizes the environmental aspects of the

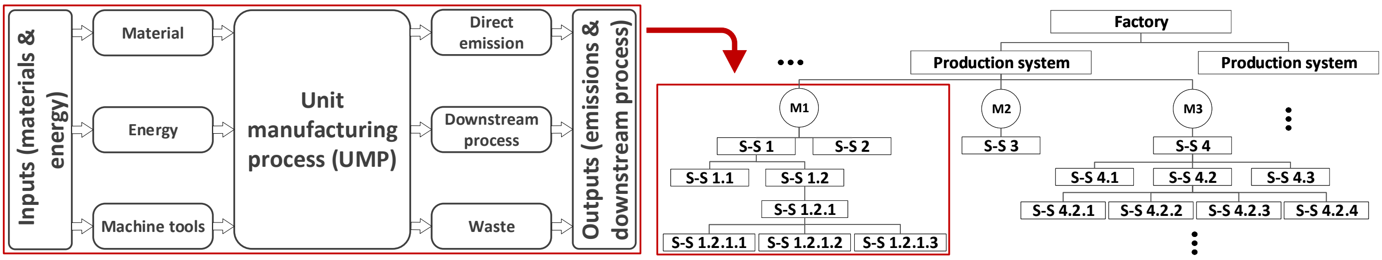

Fig. 1: (a) Overall UMP model for generic manufacturing processes; (b) Decomposition of a UMP model into subsequent components. Here, M# represents a machine tool, and S# represents a sub-system within the corresponding machine tool.

manufacturing process in additional levels of detail. The number of levels that should be considered is based on the requirement of LCI data from a specific sub-system.

3.2. Overall UMP model decomposed into component level

To determine the boundaries and limitations of the UMP model, a production system needs to be decomposed into a detailed sub-system level model, shown in Figure 1(b). The highest level of hierarchy that is considered in the decomposed UMP model is the factory-level. The next step is to decompose the model into the production systems. Subsequently, the model is further decomposed into machine-levels (M1,M2...). At the machine level, it is important to define all sub-systems (S-S1, S-S2,...). Then, the sub-systems are checked to see if they can be decomposed further. Decomposition of the process sub-systems ends when all sub-systems whose process parameters affects the resource consumption are considered. The same procedure is repeated for all other machines within the defined production system. The decomposed UMP model provides a detailed overview of all the input resources related to the specific manufacturing process and all the potential environmental impacts and outputs. The decomposed UMP model is used as a framework to build the analytical UPLCI model for estimating process resource consumption. However, further development of the UPLCI model can indicate potential limitations or deficiencies of the decomposed UMP model. To illustrate, the total energy consumption of a manufacturing process can be estimated from the power and time relationships of individual production modes. Thus, such a UMP model provides enough information about LCI data needed to carry out this estimation. However, energy consumption can also be estimated based on the process parameters that are not considered in the UMP model (e.g., based on force and velocity measurements), requiring further decomposition of the UMP model or showing its limitations. Therefore, decomposing the UMP model and formulating the corresponding UPLCI model can be an iterative process, and refinements may be required at both ends to reach alignment.

3.3. UPLCI model of manufacturing processes

This section describes the development of analytical UPLCI models used to characterize the manufacturing processes and estimate the resource consumption that depicts the environmental performance.

In this work, UPLCI models are developed based on the corresponding decomposed UMP model for a specific manufacturing process within a specific production setup. The UPLCI model development is performed in three stages:

- *Describing the manufacturing process energy characteristics*: This stage details the process characteristics through the time analysis performed to identify different production modes. Previous research has identified six different production modes that can be modified depending on the manufacturing process and operational sequences [7]. Time analysis is performed from the machine start-up to the machine switch-off, differentiating each production mode.
- *Identifying parameters affecting the energy consumption of manufacturing process*: Energy consumption of production modes is characterized as the product of power consumed in the corresponding production mode and time duration. The total energy consumption of the manufacturing process represents the sum of energy consumption of individual production modes.
- *Quantifying methods for material losses*: Apart from the time and power consumption, material consumption is also measured during the production modes. Material losses refer to waste generated from machine tool elements or workpiece material.
- *Quantifying methods for consumable fluids*: This stage quantifies fluids consumed during different production modes. Consumption is expressed per referenced flow and estimated per unit operation or a specified batch size [7].

While the developed UPLCI models indicate potential process parameters that can influence the energy consumption as well as material inputs and wastes, there is no indication as to, (i) whether these parameters can be measured for a specific process setup, (ii) there are potential uncertainties in the measurement, and (iii) the significance of a specific process parameter with regards to the aforementioned consumption and wastes. To address these limitations, the following section presents a systematic framework for assessing the *difficulty*, *variability*, and *sensitivity* (criticality) of a specific process measurement based on the UPLCI model.

3.4. DVS framework for assessment of collected data

This section describes the assessment methodology developed to identify and quantify the proposed DVS (difficulty, variability, sensitivity) framework. In order to develop this framework, we studied the challenges associated with building and applying UPLCI models to a real-world centerless grinding production setup. The framework was developed in an iterative manner and abstracted so that it could be applied to other processes. The validity of the framework was checked using discussions with process engineers and technicians and expert assessment of the applicability of the framework to two other conventional and automated manufacturing processes (plunge grinding and superfinishing) at the same facility. The studied challenges indicate the existence of influencing factors that affect the data measurement. Identifying these factors is important since they can lead to discrepancies between the UPLCI model and real-world data measurement. Consequently, we asked three questions in order to identify the factors that influence data measurement:

- **What are the production-system related factors influencing the measurement of the LCI data** A production system can be an independent unit, but in many cases, it is also a part of a centralized system that is controlled at the line- or factory-level. This can give rise to complex production architectures with hard-to-define system boundaries and sub-systems with poor data availability and accuracy.
- **What are the human related factors influencing the measurement of the LCI data?** Production systems can consist of fully- and semi-automated as well as manual manufacturing processes. Thus, human behaviour (e.g., adopted tool change practices) can significantly affect process characteristics. Moreover, operators' and technicians' knowledge and experience can impact the difficulty and accuracy of process data measurements.
- **What are the environmental conditions influencing the accuracy of the measured LCI data?** How does variability of the environmental conditions impact data measurement and data accuracy?

Based on the above questions, we identified various factors affecting the measurement of process parameters for constructing process inventory models. These factors were further divided into *difficulty* and *variability* criteria. Factors that influence the accessibility of the data and feasibility of the data measurement were classified into the *difficulty* assessment criterion, and factors that can lead to incomplete or erroneous data were grouped into the *variability* assessment criterion. Subsequently, each criterion was classified into five progressive levels based on severity of the influence. Thus, a level signifies the fulfillment of each criterion, going from the level one, where all the requirements are met, to five, where none of the requirements are met.

Secs. 3.4.1 and 3.4.2 provide a guideline for assessing the degree of difficulty and variability of process data required to build a production-specific UPLCI model. The detailed tables explaining this assessment are provided in Tbls. B.3 and B.4 in Appendix B. Sec. 3.4.3 explains the procedure for performing the sensitivity analysis.

3.4.1. Difficulty assessment

Difficulty assessment is presented through five criteria that systematically assess the various complex factors related to technological limitations of the equipment and process architecture and the impact of process knowledge on data measurement. The factors that have a significant impact are classified into five criteria.

- *Digitalization* ($C1_D$) - indicates the ease of access to the data that can be used for data analysis and real-time process control. This aspect refers to the implementation of digital data monitoring and acquisition systems for the concerned process parameters. This criterion is included in the difficulty assessment as the level of process digitalization affects the time and cost of data collection.
- *Data granularity* ($C2_D$) - indicates the availability of the concerned process parameters on the different granularity levels. Therefore, this criterion is included in the difficulty assessment as the data granularity can affect the data availability. Some portion of data may be only available at the factory/production line level, which makes data measurement on a component level difficult to perform.
- *Complexity of the process architecture* ($C3_D$) - indicates the complexity of the process architecture, which refers to the design and implementation of the process that enables direct data measurement of the concerned parameters. Consequently, this criterion is included in the difficulty assessment as the level of process architecture complexity affects the time and cost of data collection.
- *Impact of data measurement on the process* ($C4_D$) - indicates the impact that data measurement has on real-world production. Data measurement can create process disruptions during real-time production, or it can require specialized experimental setups that can affect the production output or time and cost of data collection
- *Operator/technician knowledge* ($C5_D$) - indicates the impact that operators' experience and process knowledge have on the process of data collection.

3.4.2. Variability assessment

Variability refers to all the factors that can affect the accuracy of data measurement. In the proposed framework, variability assessment is based on the following four criteria.

- *Standard operating procedure (SOP)* ($C1_V$) - a standardized process assures that there are defined sequences of operation performed with defined tools and devices in a defined time duration. Consequently, processes with well-defined SOPs have reduced cycle-to-cycle variation of process parameters such as setup time, loading and unloading time.

- *Variability of the process setup* ($C2_V$) - indicates changes in the process parameters or a production process resulting from producing a different part within the same part family. These changes can cause appreciable deviations in data measurement.
- *Variability of the environmental conditions* ($C3_V$) - indicates the internal and external factors that can impact the data measurement. Internal factors refer to machine age, tool state, and external factors include factors extrinsic to the production process, such as room temperature).
- *Reliability of the measurement* ($C4_V$) - indicates the accessibility to high-accuracy & precise data measurements or the availability of reliable empirical data.

The next section presents the sensitivity analysis performed to detect the most critical (sensitive) process parameters that affect the total resource consumption.

3.4.3. Sensitivity analysis

If the inventory data are not sensitive to a specific process parameter, there is little reason for reducing the measurement difficulty or variability for that parameter. Therefore, after the UPLCI model for a specific manufacturing process has been developed, a sensitivity analysis is performed by varying each process parameter around its nominal value by a specified percentage. Please note that the nominal value for the process parameter is determined from empirical data for that specific production setup.

4. Case Study

This section demonstrates the application of the DVS framework on a real-world through-feed centerless grinding production setup. Through-feed centerless grinding is a highly efficient material reduction process used to machine cylindrical workpieces to the fine tolerances and surface roughness. The process setup consists of three main grinding elements (i) grinding wheel, (ii) regulating wheel and (iii) work rest blade. The regulating wheel pushes the workpiece against the work rest blade while the grinding wheel removes workpiece material. In through-feed centerless grinding, a series of workpieces are continuously fed between the grinding and regulating wheel. In this case study, we applied the DVS framework for the through-feed centerless grinding of a ceramic shaft on a Cincinnati Milacron Twin Grip 3-300 machine.

Following the steps discussed in Sec. 3, we developed a decomposed UMP model as shown in Fig. 2. This UMP model was used to develop a corresponding analytical UPLCI model for the through-feed production setup. The process characteristics used for developing the UPLCI model were as follows.

1. The process starts with unloading the workpieces remaining from the previous batch and loading the feeder with workpieces from a new batch. In this case study, the feeding and conveying systems are connected and together are referred to as the handling system. During unloading and loading, peripheral systems such as the material handling system, cooling system, hydraulic system, air-suction system, and other electronics are in function. Basic time (t_{basic}) (see Fig. 3) is the time measured before the grinding and regulating wheels are started. As the peripheral systems remain operational through the entire process, it represents the basic power consumption (P_{basic}) of the centerless grinding process.
2. The grinding and regulating wheels are started after the machine is loaded with a new batch (end of t_{load_unload} in Fig. 3). Machine setup is a manual process and it is performed once at the beginning of a new batch. Setup time (t_{setup}) represents the time needed to adjust the process parameters in order to achieve defined diameter and surface roughness. The idle time (t_{idle}) corresponds to the time during which the wheels are running without making contact

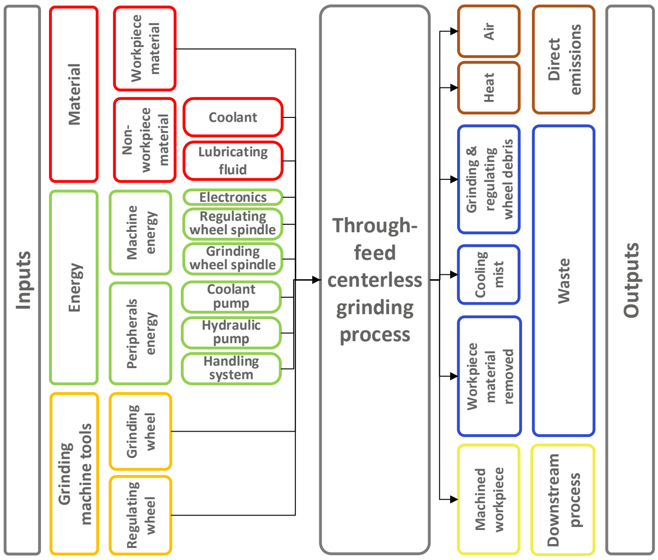

Fig. 2: Decomposed UMP model for the through-feed centerless grinding process.

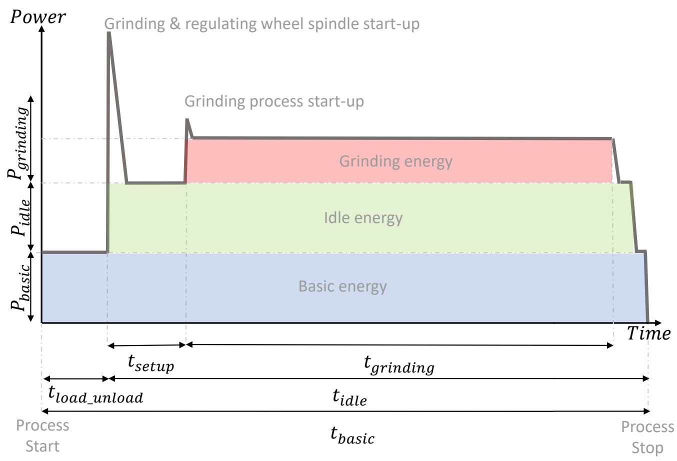

Fig. 3: Power consumption and process characteristics for the through-feed centerless grinding process.

with the workpiece. The idle power consumption (P_{idle}) refers to the power consumption of the grinding and regulating wheel spindle motors.
3. Grinding time ($t_{grinding}$) begins after machine setup (t_{setup}), when the first workpiece contacts the regulating and grinding wheels. Workpieces flow continuously throughout the process.
4. After a batch of N workpieces are machined, the machine is turned off. Dressing of the regulating and grinding wheels is not a part of the regular process and is performed during a pre-planned maintenance time.

To estimate the total process energy consumption, basic, idle and grinding energy are calculated as the product of corresponding time and power consumption, as shown in Eq. 1.

$$\begin{aligned} E_{total} &= E_{grinding} + E_{idle} + E_{basic} \\ &= P_{grinding} \times t_{grinding} + P_{idle} \times t_{idle} + P_{basic} \times t_{basic} \end{aligned} \tag{1}$$

For the purpose of this case study, only time-related parameters have been considered to demonstrate the DVS framework (see Sec. 3). These parameters are significant as they directly impact total energy consumption. Previous research also emphasizes the challenges with accurately measuring time for grinding processes [9]. Specifically, we focus on measuring idle and basic time-related parameters shown in Eqs. 2 and 3 for assessing total energy consumption.

$$t_{basic} = \frac{t_{load\_unload}}{N} + t_{idle} \tag{2}$$

$$t_{idle} = \frac{t_{setup}}{N} + t_{grinding} \tag{3}$$

The three previously explained time-related parameters (t_{load_unload}, t_{setup}, and $t_{grinding}$) were scored by an experienced process engineer who used the difficulty and variability criteria shown in the Tables B.3 and B.4 in Appendix B. Scores are shown in Table 1. The nominal values for the process parameters were determined experimentally and are shown in Appendix A.

Table 1: Difficulty and variability assessment of time-related parameters based on Tables B.3 and B.4 in Appendix B

	Criteria					
	Parameter	$C1_D$	$C2_D$	$C3_D$	$C4_D$	$C5_D$
Difficulty	t_{load_unload}	3	2	2	2	2
	t_{setup}	4	2	2	1	2
	$t_{grinding}$	3	1	2	3	2
	Parameter	$C1_V$	$C2_V$	$C3_V$	$C4_V$	
Variability	t_{load_unload}	3	1	2	1	
	t_{setup}	3	3	3	1	
	$t_{grinding}$	4	3	3	1	

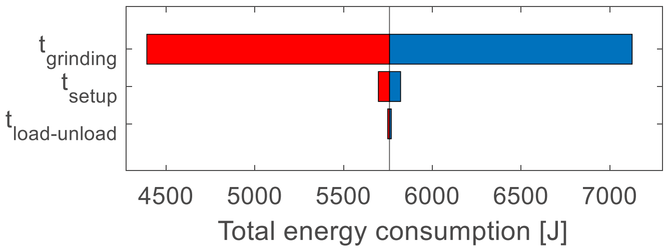

Fig. 4: Sensitivity of time-related process parameters with regards to total process energy consumption.

Fig. 4 shows the results from the sensitivity analysis of the time-related parameters with regards to total process energy consumption. As shown, a ±10% variation of $t_{grinding}$ around nominal value affects the total energy consumption by ±24%. The impact of the t_{setup} and t_{load_unload} is insignificant.

5. Results & Discussions

The difficulty assessment for time-related parameters indicates one criterion ($C1_D$) that is scored as level 3 or 4 (see Tbl. 1) due to the manual nature of the process and lack of a data acquisition system. Estimation of $t_{grinding}$ was possible only in a specialized experimental production setup. Thus ($C4_D$) contributes to the difficulty of measuring these process parameters. The non-standardized sequence of operation ($C1_V$) has a significant impact on variability assessment on all three time-related parameters, as it affects the variation of parameters from cycle to cycle. $C2_V$ and $C3_V$ for t_{setup} and $t_{grinding}$ have a significant contribution to the variability, as the changes of other process parameters (e.g. rotational speed of grinding wheel) and internal environmental conditions affect the measurement of these parameters. With regards to the sensitivity analysis, the impact of t_{load_unload} and t_{setup} on total energy consumption is insignificant (see Fig. 4) as these parameters are divided by a significantly large batch size (see Appendix A). However, sensitivity analysis performed for $t_{grinding}$ showed that the variation of the process parameter value for ±10% around the nominal value affected the total energy consumption for ±24%. Difficulty and variability assessment, along with sensitivity analysis, indicate $t_{grinding}$ as a critical parameter.

The measurement and control of this parameter should be improved to facilitate sustainability quantification and further enhancement of the studied centerless grinding process.

6. Conclusions & Future Work

This paper discussed the DVS framework that enables systematic estimation of the *difficulties*, *variablities*, and *sensitivity* associated with measurement of process inventory data from real-world production systems. The DVS framework enables process engineers and technicians to understand areas of improvement required to increase the ease and accuracy of quantifying energy and resource consumption for specific production processes. The framework was demonstrated using a real-world case study involving characterizing time-related process parameters for a through-feed centerless grinding setup. Results showed that grinding time ($t_{grinding}$) was the most critical (sensitive parameter) in terms of process energy consumption when compared to the setup and loading/unloading time. However, in the current process setup, the difficulty of measuring grinding time was significant due to its non-digitalized nature. Measuring $t_{grinding}$ required additional equipment and also caused process disruption. Furthermore, there was considerable variability due to non-standardized nature of the processes and due to the impact that changes in process parameters and internal environmental conditions had on the $t_{grinding}$. These results provide a basis for focusing process improvements (e.g., process digitalization, standardization, etc.) from the perspective of sustainable manufacturing.

As part of our future work, we will expand this study to thoroughly characterize the through-feed centerless grinding process and include the assessment of material losses and consumable fluids and their impact on total resource consumption. Our future work will also focus on applying the developed framework to other manufacturing processes, and consider the difficulties and variabilities in measuring process and inventory data across a range of process setups (automated, semi-automated, etc.). Finally, we will expand the methodology to also include identification and selection of feasible process improvements from the perspective of sustainable manufacturing.

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Appendix A.

Table A.2: Input parameters for the estimation of total energy consumption for the through-feed centerless grinding process detailed in the case study.

Power consumption	$P_g^{spindle}$=4103 W, $P_{cooling}$=590 W, $P_{hydraulic}$=1497 W, $P_{grinding}$=78 W.	$P_r^{spindle}$=594 W, $P_{handling}$=284 W, $P_{electronic}$=49 W,
Time measurement	t_{load_unload}=180 s, $t_{grinding}$=0.76 s.	t_{setup}=300 s,
Size of the batch	N	10800 pcs

For the corresponding production setup of through-feed centerless grinding process detailed in the case study, equations for estimation of P_{basic} and P_{idle} are shown in Eqs. A.1 and A.2.

$$P_{basic} = P_{electronic} + P_{handling} + P_{cooling} + P_{hydraulic} \quad \text{(A.1)}$$

$$P_{idle} = P_r^{spindle} + P_g^{spindle} \quad \text{(A.2)}$$

These equations were used to estimate basic and idle energy consumption.

Appendix B.

Table B.3: Assessment methodology for 'difficulty' in the DVS framework. Please note the each process parameter is scored individually across the five assessment criteria ($C1_D - -C5_D$).

Criteria		Difficulty				
		Level 1	Level 2	Level 3	Level 4	Level 5
$C1_D$:	Digitalization	Process has a data acquisition system with direct access to the evaluated parameter.	Process has a data acquisition system; evaluated parameter can be estimated but not directly accessed from the system.	Process does not have a data acquisition system. Digital measurement equipment can be installed to enable direct access to the evaluated parameter.	Process does not have a data acquisition system. Digital measurement equipment can be installed; evaluated parameter can be estimated but not directly accessed from the equipment.	Process does not have a data acquisition system and it is not possible to install any additional equipment to estimate the evaluated parameter.
$C2_D$:	Data granularity	Possible to measure the evaluated parameter at the highest granularity level, e.g., component / sub-system level.	Only possible to measure the evaluated parameter at intermediate granularity, e.g., machine level.	Only possible to measure the evaluated parameter at low granularity, e.g, production system level.	Only possible to measure the evaluated parameter at very poor granularity e.g., factory level.	Not possible to measure no the evaluated parameter at any level of granularity.
$C3_D$:	Complexity of the process architecture	The process architecture is designed & implemented to enable direct measurement of the evaluated parameter; measurement is simple & time/cost efficient.	The process architecture needs minor modifications in order to enable direct measurement of the evaluated parameter; modification is simple & time/cost efficient.	The process architecture enables indirect estimation of the evaluated parameter. Significant modifications are need to enable direct measurements.	The process architecture enables indirect estimation of the evaluated parameter. The process cannot be modified to enable direct data measurement.	The process architecture does not allow direct measurement or indirect estimation of the evaluated parameter; no process modification is possible.
$C4_D$:	Impact of data measurement on the process	Measurement process for the evaluated parameter can be performed during production, without creating any process disruptions.	Measurement process for the evaluated parameter disrupts production; disruptions are minor and can be ignored.	Measurement process for the evaluated parameter disrupts production; managing the disruptions require some process alterations.	Measurement process for the evaluated parameter requires specialized experimental setups outside regular production.	Measurement process for the evaluated parameter is not possible on the production setup.
$C5_D$:	Operator/ technician knowledge	Operators have in-depth knowledge of the production setup and experience with measurement of the evaluated parameter.	Operators have good knowledge of the production setup and some experience with measurement of the evaluated parameter.	Operators are familiar with a similar production setup in another line/factory. They have some experience with measurement of the evaluated parameter.	Operators have limited familiarity about the specific production setup and similar setups. They have no experience with measurement of the evaluated parameter.	Operator knowledge is inaccessible due to lack of access to the operator or production line.

Table B.4: Assessment methodology for variability in the DVS framework. Please note the each process parameter is scored individually across the four assessment criteria ($C1_V - -C4_V$).

Criteria		Variability				
		Level 1	Level 2	Level 3	Level 4	Level 5
$C1_V$:	Standard operating procedure (SOP)	Sequence & procedure of operations relevant to the evaluated parameter is completely described in an SOP; operations are performed in a defined order using the exact methods and tools stated in the SOP.	Sequence & procedure for a majority of operations relevant to the evaluated parameter are described in an SOP; operations standardized in SOP are performed as defined while the rest are performed based on formal agreements between operators / engineers.	Sequence & procedure for some operations relevant to the evaluated parameter are described in an SOP; operations standardized in SOP are performed as defined while the rest are performed based on formal agreements between operators / engineers.	No operations relevant to the evaluated parameter are defined in an SOP. However, they are based on formal agreements between operators / engineers.	No operations relevant to the evaluated parameter are defined in an SOP. Operations are performed based on the judgement of individual operators.
$C2_V$:	Variability of the process setup	Changes in the process parameters or the production process for producing another part within the same part family do not impact measurement of the evaluated parameter.	Changes in a process parameters or the production process for producing another part within the same part family have a known impact on measurements of the evaluated parameter; it is possible to control and monitor the impact.	Changes in a process parameters or the production process for producing another part within the same part family have a known impact on measurements of the evaluated parameter; impact can be monitored but not controlled.	Changes in a process setup or the production process for producing another part within the same part family have a known impact on measurements of the evaluated parameter; impact cannot be monitored or controlled.	Changes in a process setup or the production process for producing another part within the same part family have an unknown impact on measurements of the evaluated parameter; impacts are difficult to trace.
$C3_V$:	Variability of the environmental conditions	Production occurs in controlled environmental conditions that do not have any impact on the evaluated parameter.	Production occurs in controlled environmental conditions that have a known impact on the evaluated parameter; the impact is monitored and controlled.	Production occurs in controlled environmental conditions that have a known impact on the evaluated parameter; the impact is monitored but not controlled.	Production occurs in uncontrolled environmental conditions that have a known impact on the evaluated parameter; impact is not monitored or controlled.	Production occurs in uncontrolled environmental conditions and their impact on the evaluated parameter is unknown and difficult to trace.
$C4_V$:	Reliability of the measurement	The evaluated parameter can be accurately measured on the production line (or) reliable empirical data for the evaluated parameter is available for the specific production setup.	Measurement of the evaluated parameter from the specific production line requires assumptions or approximations based on reliable empirical evidence.	The evaluated parameter cannot be measured from the specific production line. However reliable empirical data is available for a generic production process.	It is only possible to measure the evaluated parameter based on qualified estimates from experts; no reliable empirical data is available.	No reliable estimates can be made for the evaluated parameter.