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Feature selection for constructing datasets toward automated lifecycle assessment for additive manufacturing

Ahmed Z. Naser, Fantahun Defersha, Sheng Yang
School of Engineering, University of Guelph, Guelph (ON), N1G 2W1, Canada
anaser@uoguelph.ca, fdefersh@uoguelph.ca, syang19@uoguelph.ca

Abstract — Additive Manufacturing (AM) is considered an innovative technology to fabricate goods with green characteristics. In comparison to conventional manufacturing (CM) approaches, AM technologies have shown impressive results in enhancing sustainability in production systems. Various research has been conducted to assess the environmental impacts of AM based on the well-known life cycle assessment (LCA) framework. However, this approach requires intensive domain knowledge to build the environmental impact model and interpret the impacts of input variances. This knowledge barrier may cause delays and challenges in the selection of the optimal design and process parameters for additively manufactured parts in the product design and planning stages due to the iterative design-evaluation process. As such, the research community demands an automated LCA tool for supporting AM toward elevated sustainability. To achieve this ambitious goal, this paper particularly investigates the fundamental question – "What are the key influential parameters that pose an impact on the environmental sustainability of AM?". A methodological framework for identifying the key influential parameters for AM is proposed. The framework was demonstrated by taking the fused filament fabrication (FFF) process as an example. Based on instantiation, LCA of over 200 AM instances, and correlation analysis, the key influential parameters are identified. Finally, a dataset with the identified features could be constructed. This dataset is expected to establish a common base for scale-up with joint efforts from the AM community.

Keywords- additive manufacturing; life cycle assessment; machine learning; feature selection

I. INTRODUCTION

Additive manufacturing (AM) is a layer-based automated fabrication process for producing scaled 3-dimensional (3D) physical objects directly from 3D Computer-Aided Design (CAD) data without the use of part-dependent equipment [1]. Due to the limitations of conventional manufacturing (CM) processes such as milling and turning, the increasing possibilities of AM have opened the doors to pursue new design ideas that can be transformed into products in a faster, greener, and more efficient way [2]. In comparison to CM, AM offers significant sustainability potential. This is because it requires less raw material in the supply chain process, which leads to eliminating tooling, scraps, and non-environmentally friendly enablers. Moreover, AM allows the production of parts with lighter weights, which can enhance fuel efficiency and minimize carbon emissions in the service life of aircraft and automobiles. Due to AM's ability to promote decentralization and close-to-consumer manufacturing, this technology can also reduce the carbon footprint and pollution associated with long transportation distances. Further, supply chain operations related to new tooling production can be also eliminated via AM, allowing failed tools' reparation and remanufacturing [3–5].

Data mining and Machine Learning (ML) have become important research topics in the manufacturing field. The creation of knowledge-based system architecture for sustainable manufacturing has become a vital issue [6]. Today, ML has been employed in many sustainable manufacturing fields such as process parameters optimization [7,8], energy/power consumption modeling [9,10], sustainable planning and scheduling [11–13], energy prediction modeling for machine tools [14], and quality control [15,16]. However, there are rarely known efforts invested in employing ML toward sustainable AM.

With the ambitious goal of developing an automated life cycle assessment (LCA) tool to support sustainable AM design and process, this paper mainly concentrates on answering the question - "What are the key influential parameters that pose an impact on the environmental sustainability of AM?". These key influential parameters can be used as the features for constructing an open-source dataset for supporting data sharing and scale-up for data mining and ML applications for sustainable AM. The paper is structured as follows. Section 2 provides a review of the different environmental impact assessment methods for AM as well as applications of ML for LCA. Section 3 introduces the proposed methodological framework to identify the key influential parameters which significantly affect the environmental performance of AM. Section 4 presents the correlation analysis results along with the list of key influential features. This section also provides a research direction toward a more refined list of key features.

Finally, section 5 includes concluding remarks and future research directions.

II. LITERATURE REVIEW

Various approaches have been used to quantitively assess the environmental impacts of AM. Some of these approaches include LCA, Design for Environment (DfE), and Environmental Impact Scoring Systems (EISS) [17]. Yet, the most widely used methodology for the evaluation of the environmental impacts of a product's entire life cycle is LCA [5]. In comparison to other methodologies such as Carbon Assessment or DfE [18], LCA has the ability to quantify the environmental impacts of a global system in a precise way and with diverse criteria [19]. Many studies have been reported on using LCA tools to assess the environmental performance of AM processes. These studies can be categorized into unit process modeling [20-22], studies comparing the environmental impacts between two or more AM technologies [23,24], or between AM technology and CM [25-27]. Other studies were only based on comparing the energy consumption between two or more AM technologies [28,29] or comparing the energy and/or material consumption between AM technologies and CM [30,31]. These studies vary in the type of AM technologies, the scope of LCA considered (e.g., cradle to gate, cradle to grave, etc.) as well as the resources they chose (e.g., material, energy, transportation, etc.) to evaluate the environmental impacts. Furthermore, they also differ in whether embodied energy of 3D printers, auxiliary tools, and post-processing were included in the analysis or not [32].

Yet, utilizing the LCA tool can be challenging. This is attributed to the fact that LCA requires detailed extensive knowledge to conduct and can be time-consuming and expensive to perform [32]. Furthermore, interpreting LCA results demands extensive expertise, and providing answers to simple "what if" questions can take a lot of back-and-forth waiting and reporting which may sometimes delay critical investment decisions [33,34]. Another challenge of LCA is the highly demanding procedure of data collection for process and life cycle inventories [35]. LCA can be visualized as a black box tool, making people hesitant to rely on it [36]. Such a data-intensive procedure can be inefficient at the early process design stages where a lot of required background and foreground inventory data are still missing [35].

Therefore, several studies in the literature have investigated the feasibility of coupling LCA with ML to develop automated alternative methods to support decision-making processes during the planning and designing stages and provide assessments that can be conducted "ahead of detailed design" [37,38]. When integrated with LCA, ML has been proven efficient in predicting and significantly reducing the environmental impacts of buildings [37] as well as estimating the life cycle impact of chemicals [39]. Nonetheless, the research community still lacks studies on the feasibility of ML algorithms to predict the environmental impacts of the AM process. This might be attributed to various challenges, one of which is the lack of knowledge in selecting key influential features.

III. THE PROPOSED METHODOLOGY FOR IDENTIFYING THE KEY INFLUENTIAL FEATURES

Figure 1 depicts the proposed methodology for identifying the key influential design and process features that affect the environmental performance of AM process.

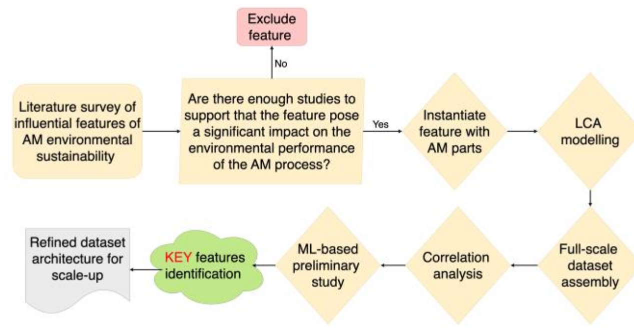

Figure 1. The proposed methodology for identifying the key influential features.

The first step involved reviewing the literature to decide upon all the features/parameters that can pose such an effect. By using query keywords "sustainability or environment" AND "additive manufacturing or 3D printing" AND "Year 2010-2022" on both "Web of Science" and "Google Scholar", over 520 articles were found. By filtering out repeated, conference papers, and articles that do not study the relationship between process or design parameters with environmental impacts, only 145 papers were selected for further reading. From the surveyed literature, ten design parameters/strategies (i.e., part volume/volume fraction, cross-sectional area, surface area, base area, Z-height, weight, shape complexity, orientation, material, number of parts/assembly interfaces) and sixteen process parameters (i.e., air gap, batch size/ part's packing, deposition speed, scanning/printing speed, infill density/filling rate, laser power, layer thickness/ slice height, nozzle and platform temperatures, powder feed rate, powder flow rate, printing path, printing resolution, raster angle, road/raster/bead width, and support related strategies) were found to pose an impact on AM's environmental sustainability. Figure 2 shows these parameters along with their associated number of studies. It can be observed that the part's orientation and layer thickness are the most widely studied design and process parameters respectively. On the other hand, some parameters are much less investigated such as base area, cross-sectional area, air gap, etc. This might be attributed to the low impacts of these parameters on the environment and/or the need for more in-depth studies to better understand their effect on AM's environmental performance. In any case, these parameters were excluded from further investigation in this study. Since the remaining parameters vary for different AM processes, this paper takes the fused filament fabrication (FFF) process as the research object. As such, five AM design features (i.e., part volume, weight, Z-height, surface area, and filament density) and seven AM process features (i.e., layer thickness, printing speed, printing and platform temperatures, infill density, support height, and support volume) were considered for further investigation in the third step (i.e., instantiation in Figure 1).

Next, these twelve parameters were instantiated with eleven different parts. These parts varied in their shapes' complexity (i.e., some of these parts have been topology optimized (e.g., shelf bracket) while others have been optimized using cellular structure (e.g., connecting rod and quadcopter). For each part, two different building orientations were considered, and two different filament materials were investigated: ABS and PLA. Overall, 200 data points have been obtained. For each data point, the material consumption and printing time were evaluated using the open-source software Ultimaker Cura®. These obtained data were then fed into the fourth step – LCA modeling to measure the corresponding environmental impacts.

In LCA modeling, the functional unit was defined as a one count of an additively manufactured part with a specifically defined volume. The system boundary was defined as gate to grave, that is the reception of raw materials to the end of life. Figure 3 depicts the LCA model for a quadcopter part [40] with the material and energy flows within the process and system boundary.

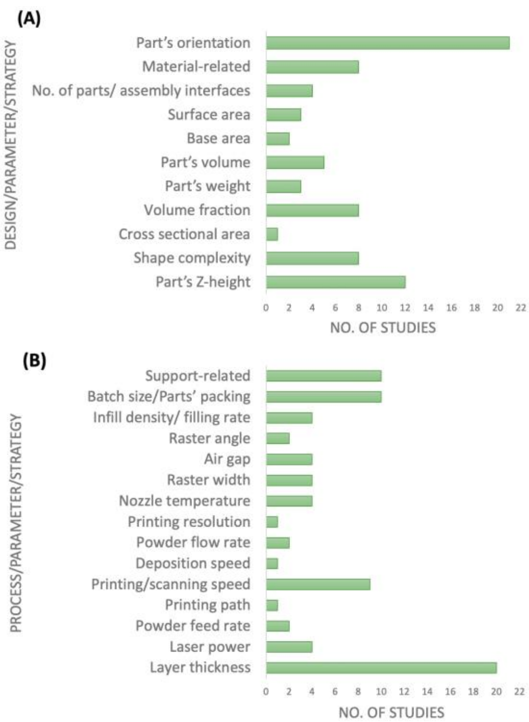

Figure 2. Summary of the various AM (A) design, and (B) process parameters that pose an impact on the environmental sustainability of the process along with their associated studies.

The developed LCA model covered the following processes: reception of the raw materials, plastic production, extrusion of the 3D filament, AM process, and recycling of the wastes. PLA/ABS plastic production process was modeled using the integrated production process in the GaBi ts LCA software. The filament extrusion process was modeled using the total material consumption as the input, and the outputs consisted of the same amount of material as extruded filament. The AM process was modeled taking into account the energy consumption and the extruded filament as inputs while the outputs consisted of the finished part and support structures. Finally, 34% of the total material consumption was assumed to be recycled [41]. The environmental assessment was conducted according to the characterization factors reported in the ReCiPe (World-H) 2016 midpoint method. A total of 18 impact indicators were collected for each feature data entry. With the aid of the previous steps, a training dataset that consists of the 12 design and process parameters as the features/inputs and the 18 environmental impact categories as the target variables/outputs was obtained. A sample datapoint of the established training dataset is shown in Table 1.

Following that, correlation analysis was employed to spot redundant features. In this study, Pearson standard correlation coefficient was used to measure the correlation between features. Pearson correlation coefficient is defined as the ratio between the covariance of two variables and the product of their standard deviation [42]. Unlike other dimensionality reduction

Table 1. A sample data point (for the quadcopter part) in the developed training dataset.

AM design features		
Feature	**Unit**	**Amount**
Part volume	cm^3	11.93
Part weight	N	0.145
Part Z-height	mm	20.56
Part surface area	cm^2	432.8
Filament density	g/cm^3	1.24 (PLA)
AM process features		
Feature	**Unit**	**Amount**
Layer thickness	mm	0.1
Printing speed	mm/s	50
Printing temperature	°C	210
Platform temperature	°C	60
Infill density	%	20
Support height	mm	16.373
Support volume	cm^3	15.081
LCA environmental impacts		
Impact category	**Unit**	**Amount**
Climate change	kg CO_2-eq to air	0.11
Fine particulate matter formation	kg PM2.5-eq to air	0.0000473
Fossil resource scarcity	kg oil-eq	0.0214
Water use	m^3 water-eq consumed	0.173
Freshwater ecotoxicity	kg 1,4-DCB-eq to freshwater	0.000202
Freshwater eutrophication	kg P-eq to freshwater	0.000000341
Human toxicity: cancer	kg 1,4-DCB-eq to urban air	0.00165
Human toxicity: non-cancer	kg 1,4-DCB-eq to urban air	0.00171
Ionizing radiation	kBq Co-60-eq to air	0.000638
Land use	m^2 × year annual cropland-eq	0.0396
Marine ecotoxicity	kg 1,4-DCB-eq to marine water	0.000119
Marine eutrophication	KgN-eq to marine water	0.0000032
Mineral resource scarcity	kg Cu-eq	0.000696
Photochemical oxidant formation: terrestrial ecosystems	kg NOx-eq to air	0.000184
Photochemical oxidant formation: human health	kg NOx-eq to air	0.000183
Ozone depletion	kg CFC-11-eq to air	0.000000102

Terrestrial acidification	kg SO_2-eq to air	0.000144
Terrestrial ecotoxicity	kg 1,4-DCB-eq to industrial soil	0.014

methodologies (i.e., principal component analysis), correlation analysis does not involve any transformed features. As such, it does not affect the interpretability of the original features and does not lead to data variability loss. Pearson coefficient has been proven effective in spotting the correlation between features in several studies [42-44]. The last part of the proposed methodology involves conducting a ML-based preliminary study for a more robust feature selection evaluation.

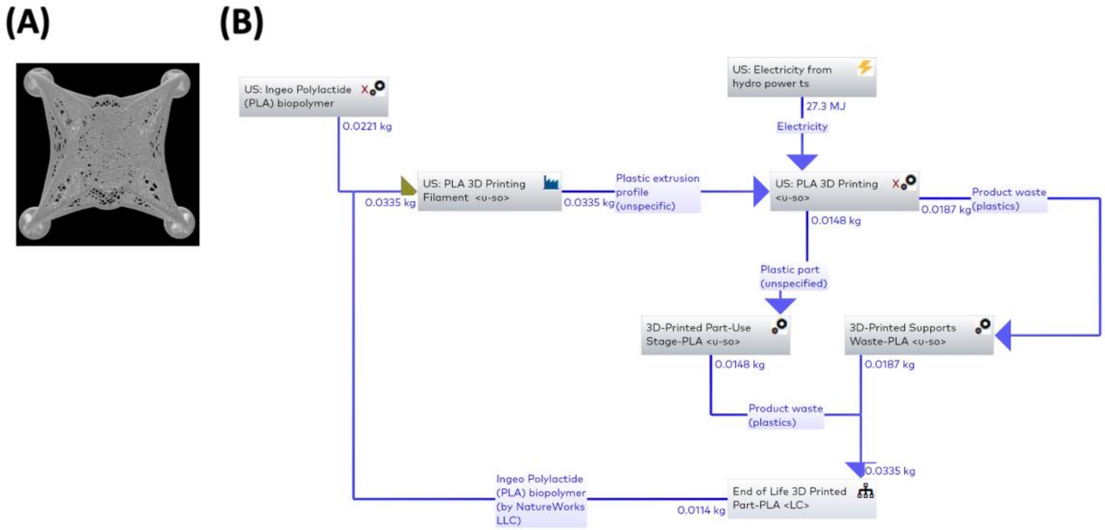

Figure 3. The quadcopter part [40] (A), and LCA model for the quadcopter part with material and energy flows in the system (B).

IV. Results of the correlation analysis

Figure 4 depicts a heat map for the correlation analysis result. Taking a closer look at the results shows that both: the printing/nozzle and platform temperatures demonstrate a perfect positive correlation (+1.0). Furthermore, the density of the filament exhibits a perfect negative correlation (-1.0) with the platform and printing temperatures. Since the material's type/density determines the printing and platform temperatures, it might seem logical to sacrifice these two temperatures from the refined list of key features. This is also supported by the fact that these features reflect the same correlation coefficient values with respect to the 18 target variables. Results also suggest that the Z-height of the part is very highly correlated (0.9-1.0) with the support height. Thus, it might make more sense to drop the support height from the refined features list since the Z-height of the part determines the height of the supports. Part weight and volume also exhibit a very high correlation. Looking at the heat map, the correlation coefficient values of each of these two features with each of the 18 target variables are very close, hence no definite conclusion can be reached on which of these two features can be dropped. On the other hand, there exists a moderate correlation (0.5-0.7) between the support volume and part surface area. A moderate correlation also exists between the infill density and both the part weight and volume. The same is also applicable to the part weight, volume, and surface area. The correlation heat map can also give insights into the correlation between features and target variables. The majority of the target variables exhibit a high correlation (0.7-0.9) with the part weight, volume, support volume, and a moderate correlation with the surface area. Thus, we recommend refining the list of key influential features from twelve to nine features only: five of which are AM design features (part Z-height, volume, weight, surface area, and filament density), while the remaining four are AM process features (layer height, printing speed, infill density, and support volume).

Nonetheless, the limitation of this type of analysis is that even though it does not affect the interpretability of the original features, it cannot determine the causality between two independent variables. Thus, for a more robust feature selection evaluation, a preliminary study using various ML models with various trials corresponding to various combinations of the very high, high, and moderately correlated features is needed. For example, the first iteration can involve evaluating the performance of the model using all the 9 identified key features. In the second and third iterations, the model's performance should be evaluated using 8 features (i.e., one of the part weight and part volume, which are very highly correlated, should be removed in each iteration). Since the 18 impact categories are continuous variables, a simple regression prediction model might be a good idea to start with and consider as a baseline model. The next step can involve evaluating the performance of other supervised learning regression ML models (i.e., random forest regressor, extreme gradient boosting (XGBoost), and deep neural network) relative to the baseline model. Based on the robustness of the various models corresponding to the different trials of this preliminary study, a more refined and final list of key influential features is anticipated. This final list can then be used to build a ML-based environmental impacts predictive model for the FFF process.

V. CONCLUSIONS AND FUTURE RESEARCH DIRECTIONS

This paper has presented various LCA-based approaches in which the environmental impacts of AM have been assessed. The lack of knowledge in deciding upon key parameters in AM is one of the major challenges that hinder automating the LCA for AM. Thus, a methodology was proposed to tackle this obstacle. The proposed methodology was demonstrated using the FFF process as an example. With proper modifications, the proposed framework can be also generalized to other AM technologies. Future research directions may include assessing the current database for overfitting/underfitting, testing, and comparing the performance of various supervised ML algorithms in predicting the environmental impacts of AM. Based on the outcomes of this future research, an expansion of the current database might be necessary if performance is inadequate. Finally, automating the feature extraction process is also a recommended opportunity for future research.

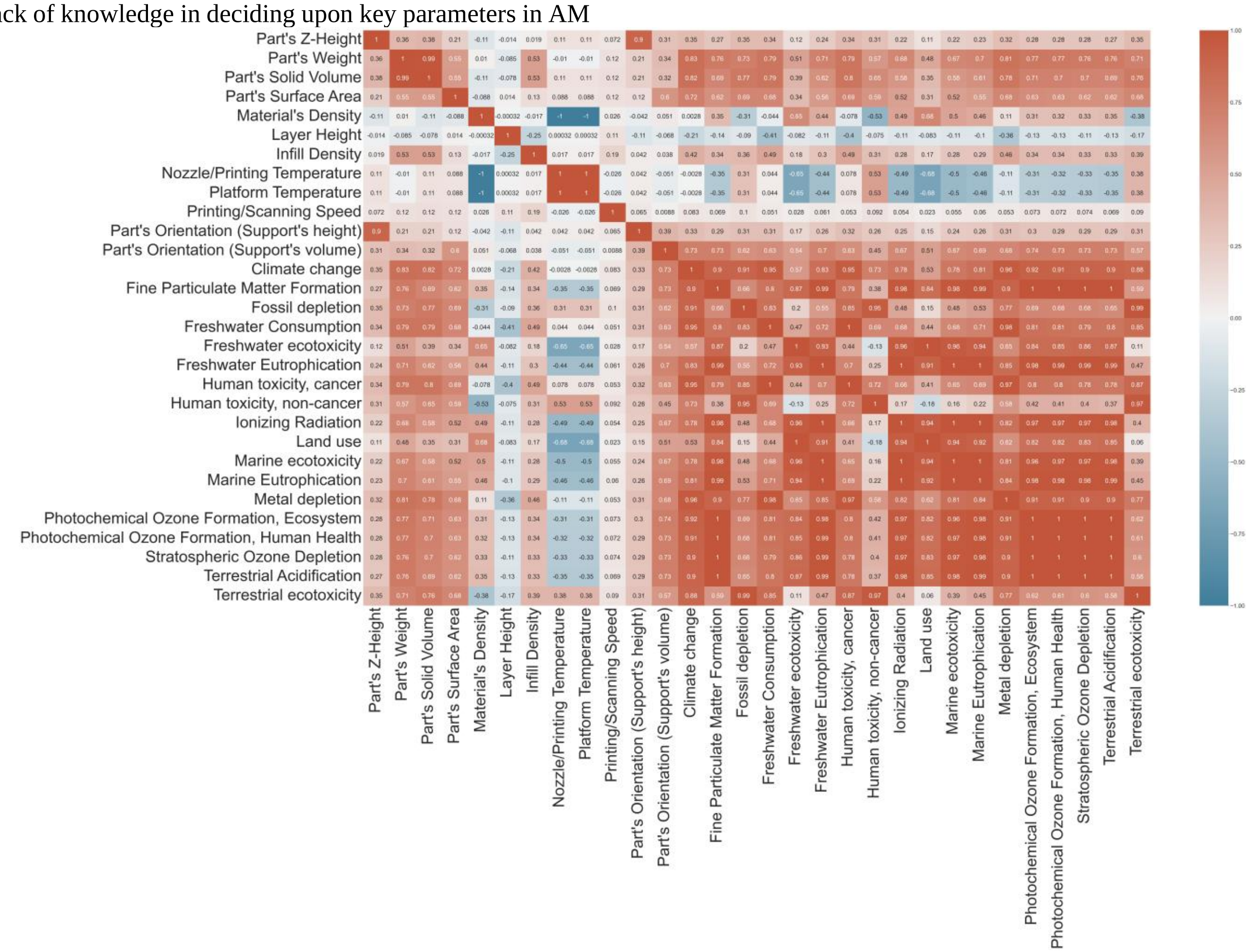

Figure 4. Correlation analysis heat map.

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