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ENERGY AND EMISSION ESTIMATION UNCERTAINTY IN FUSED DEPOSITION MODELING FOR A JOB-SHOP

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Abstract

Solid freeform fabrication has the potential to affect both financial and environmental concerns for manufacturing enterprises. However, when planning for installation of a new machine tool, accurate energy usage estimation relies heavily on the data and model selections of the estimator. This project used a variety data sources and model decision options to examine the spread of energy consumption and global warming potential estimates for a fused deposition modeling machine. In addition to primary and secondary data sources, the use of similar machines was explored as proxy estimates for the target machine. A Monte Carlo simulation was constructed to vary the model selections, machine utilization, and data sources. The results indicated data sources and model decisions had large effects on the output and that most model estimates were low.

Introduction

The manufacturing industry is ever-growing more conscious of the triple-bottom line (financial, environmental, and social impacts) of production activities. In addition to awareness, increased instrumentation of machine tools provides data to better assess each impact area. One commonly employed technique to evaluate any, or all, of these impact areas is Life Cycle Assessment (LCA), where the inputs and outputs of each process in each life cycle phase are tabulated [1]. The tabulated results typically provide point estimate of the impact, but often lack sufficient information about uncertainty in the result to be widely useful. Although many methods have been proposed to address uncertainty issues in LCA point-estimates, no clear solution has been accepted in the literature [2] [3] [4] [5].

Uncertainty in this document is categorized into three areas 1) parameter, 2) model, and 3) scenario, following [6]. First, *parameter* uncertainty arises from inaccuracy of the value(s) assigned to each variable, or parameter, in a given model. Parameter uncertainty stems from inherent randomness of the process, assignment of data from proxy technologies/machines, error in collected test data, and non-representative data for the population in question. Second, *model* uncertainty is attributed to simplification of process physics, negligence of pertinent processes or inputs, and incomplete or inaccurate process knowledge. Third, *scenario* uncertainty comes from the use of aggregate data which assumes homogeneity and sourcing data from inadequately representative processes or exclusion of relevant data. Scenario uncertainty could be ignoring pertinent the geographical, temporal, or technological specifics of the system in question.

When uncertainty is included in a LCA, typically only parameter or scenario uncertainty have been considered. Some proposed qualitative methods for evaluating input data sources [7]

[8], but fail to add significant value in comparing results or quantitative risk assessment. More robust methods for incorporating uncertainty involve statistical simulation [9] [10] [11], but typically only vary the values of predetermined parameters in a single fixed model. Many LCA studies do not address the issue of uncertainty, some avoid interpretation errors [12]. Thus, a more comprehensive inclusion of uncertainty in LCA is needed to ensure usefulness of the results. Namely, a statistical simulation that includes model variations can illustrate the variety of estimates that may be generated for a single assessment. Environmental impacts are often reported using a variety of metrics which represent the potential for environmental damage. In this work, only gaseous emissions that contribute to climate change were considered, historically tabulated as carbon-dioxide equivalent mass and named Global Warming Potential (GWP) [13]. The recent interest in Additive Manufacturing and 3D printing, but limited work assessing sustainability, makes the case study on Fused Deposition Modeling (FDM) in this paper highly relevant.

The objective of this study was to examine the combined effects of parameter, scenario, and model uncertainty in predicting the energy usage and associated global warming potential of parts made on a FDM machine in a Northern California job shop.

Methodology

This methodology is separated into two main sections the first describes the prediction scheme and second describes data collection. The prediction scheme includes how the simulation of energy intensity and GWP estimates were conducted, the *models*. The prediction scheme allowed for data at different levels of granularity, *scenarios*. For example, the U.S.A. national average cost per kilowatt-hour of electricity was less precise of a proxy than the California average for estimating energy costs for a machine installed in Berkeley, California. Since the actual implementation details of a target machine are not necessarily known in a general application, proxy estimators were included. The data collection section provides how power measurements were taken and what literature data was included.

Prediction Scheme

A variety of *scenarios* may exist for the installation and operation of a given machine tool. Similarly, literature estimates for a single machine tool implementation may encode these differences due to investigator knowledge, literature completeness, devoted study time, and invested resources. To model this variety, several combinations of data sources represented varying degrees of 1) scope of included elements, 2) proxy appropriateness, and 3) investment in the estimate. The scope of an estimate determines which major components are included, here major elements were denoted Value Add Process, Machine Auxiliary Processes, HVAC, and Lighting. Each iteration of the scope in the simulation was expanded by including an additional component (Table 1). The selected proxies were chosen to represent plausible data sources of similar technology, another FDM machine, and a photopolymer-jetting machine. Each unique combination of the data sources represents a single *scenario*. Practitioners may favor different models and data sources, this was captured by iterating over several options within each defined scope (Table 1). To capture this variety, at each *Scope*, common models were considered separately for each *Component* (Table 2). Each unique combination of *Scope*, *Scenario Model*, and *Data Source* represents a set of point estimates.

While the *Scenario Models* in Table 2 provide a high level description of the calculation, the details follow. Energy was defined as the integral of instantaneous power over time. This was discretized into a sum over the various contributing energy sources, listed as *Components* in Table 1 and Table 2. For generality, the energy delivery efficiency, denoted η, was broken down into extraction from raw materials, transportation of the extracted materials, conversion into electricity, and finally transmission to the machine. However, since all of the machines considered in this study received energy from the same system this delivery efficiency was extracted from the sum as a constant, η_{total}. Energy per kilogram of part produced is equivalent to the sum of instantaneous power consumption, P, over the time, t, required to produce the part (Equation (1)). This was further broken down to include the energy consumed by the machine, $E_{machine}$, the heating, ventilation and air-conditioning (HVAC), E_{HVAC}, and the lighting allocated to the machine, $\mathrm{E}_{\text{lighting}}$ (Equation (1)).

$$E := \int P dt \cong \sum \frac{P_i t_i}{\eta_i} = \frac{(E_{HVAC}+E_{machine}+E_{lighting})}{(\eta_{transmit}\eta_{conv}\eta_{transport}\eta_{extract})} \tag{1}$$

The *Value Add* process is denoted *production* in the subscripts of the equations (Equations (2) and (3)). This *production* and *additional machine processes* for FDM and Photopolymer Jetting were discretized into a warm-up, production, idle, and standby operational phases with differing time lengths following the work of [14]. Each operational phase duration was scaled by the total of the phases to provide a utilization, or duty cycle, for the machine. The time to complete a given job is also varied in accordance with the range of job sizes collected over the course of the sample period, denoted t_{job}, with the average length $\bar{t}_{job}$. This duration of t_{job} then provided the length of time needed to deposit one kilogram of material based on the previously determined utilization. Adjusting the time lengths in this manner was to apply the energy used during down time of the machine to the products it produced.

$$E_{machi} = \left(\frac{P_{production}t_{production}+P_{idle}t_{idle}+P_{standby}t_{standby}+P_{warm-}\quad t_{warm-up}}{t_{total}} t_{job}\right)\frac{1}{\eta_{total}} \tag{2}$$

The ambient temperature control (HVAC) and lighting in the facility were allocated to all of the machines according to the models listed in Table 2 with data from [15] [16] (Equation (3)). Where the Square Footage model means the total power used by the metered HVAC system was applied equally over the area used by the machine and auxiliary components. The Thermal Load model used the waste heat, Q, generated by the machine during each operational phase and assumes the HVAC system must counter this energy load (Equation (3)).

$$E_{HVAC} = \frac{1}{\eta_{total}} \begin{cases} P_{HVAC}\dfrac{A_{machi}\quad +A_{auxiliaries}}{A_{metered}}\bar{t}_{job} \\ \left(\left(\dfrac{Q_{production}t_{production}+Q_{idle}t_{idle}+Q_{standby}t_{standby}+Q_{warm-up}t_{warm-up}}{t_{total}}\bar{t}_{job}\right)\right. \end{cases} \tag{3}$$

Once the scenarios were defined, a Monte-Carlo simulation was then conducted using MATLAB. For each scenario, each parameter from each data set was conditioned with a probability distribution. Since many of the available data sources provided either a mean and standard deviation, or just the range of values the probability distribution is not known. Thus, probability distributions were selected among Uniform, Gamma, Normal, and Lognormal as an additional model variation (Table 3). When mean and variance are provided, the maximum and minimum values were set to 5 standard deviations away from the mean value. Similarly, when only a maximum and minimum value were provided, the mean was set as the average of the two values and the minimum set as 3 standard deviations below the mean. Fixing the relations of minimum value and mean value allowed for calculation of probability distribution factors where appropriate.

Table 1. Resource consumption analysis boundary conditions, or scopes. Each subsequent scope includes the components of all previous scopes.

Scope	*Component Added*	*Item(s)*
1	Value Add Process	Energy
2	Additional Machine Processes	Energy
3	HVAC& Lighting	Energy

Table 2. Energy consumption component scenarios specifying data sources and scenario model decisions.

Component	*Number*	*Scenario Model*	*Data Source*
Machine & Auxiliaries	A	Measurement	Primary
	B	Data Sheets	Machine Suppliers
	C	Industry Average	National Data Set
HVAC	0	No Contribution	n/a
	1	Square Footage	Primary
	2	Thermal Load	Estimated
Lighting	I	No Contribution	n/a
	II	Square Footage	Primary

Table 3: Summary of probability distributions used to condition parameter values

Distribution	Form	Representation
Uniform	$F(x,a,b) = \frac{x-a}{b-a}; x \in \{a,b\}$	Enforces the least information on variance of the estimate, but over a fixed interval
Gamma	$F(x,\alpha,\beta) = \frac{1}{\Gamma(\alpha_\Gamma)} \int x^{\alpha-1} \frac{e^{-\frac{x}{\beta}}}{\beta^\alpha}$	Ensures only real positive values with no upper bound, but mode is more flexible than the lognormal
Normal	$F(x,\mu,\sigma) = \Phi\left(\frac{x-\mu}{\sigma}\right)$	Mathematical limit of most measurements, unimodal

Lognormal	$F(x,\mu,\sigma)=\Phi\left(\frac{\ln x-\mu}{\sigma}\right)$	Ensures only real positive values with no upper bound

For each conditioned parameter 5000 samples were taken from the chose probability distribution from Table 3. The parameters were then combined according to the selected model for each component and the energy and GWP values totaled. GWP was calculated by multiplying the energy values by the weighted sum of GWP factors for the selected data set. Different energy sources had different GWP factors and they were combined prior to multiplication. The majority of the simulation used a single probability distribution for all of the parameters, selected from Table 3. One additional distribution of estimates was generated making selections more specific to the 'target' machine. This target machine served as a datum to compare all other estimates and represents the narrowest bounds on the estimated results.

Data Collection

Power Consumption Measurement

Energy consumption was efficiently collected by characterizing the machine tool energy usage by operation phase. A Yokogawa CW240 placed in between the machine power cord and the wall outlet on the shop floor. Each machine was used normally in the course of the machine shop business. During the course of operation output mass and time of production were recorded for 6 weeks. The process for this energy characterization was inspired by the Baseline Energy Consumption model from [17]. Clemon, et al., adapted this model for additive manufacturing in FDM and Photopolymer-jetting machines [14] [18]. Thus, the amount of data required to determine the energy consumption of each machine was greatly reduced without significant loss of granularity. Machine operation was characterized into several operational phases. The operational phases for sorting energy data include warm-up, idle, production, and standby. For each build, energy demands were averaged based on operation phase. The variation recorded in the data provided a variance for demand in each phase. Further, the minimum and maximum uptime for the machine over the recording period provide a percentage and range of utilization for the simulation. Uptime is collected from the machine on-board job log.

Environmental Impact Estimate

Three environmental impact scenarios were considered for Global Warming Potential (GWP) emissions, measured by carbon dioxide equivalent weight for greenhouse gases, due to energy consumption. The first emissions scenario, denoted G1, was the estimated impact according to an Economic Input-Output (EIO) analysis. EIO analysis uses information from the U.S. Commerce and U.S. Environmental Protection Agency in concert for a linear estimate of the GWP per kWh purchased from the power sector [19]. The second GWP scenario, G2, used data on the upstream and downstream externalized effects of power delivery from a report by the National Academy of Sciences [20]. This report provided energy delivery efficiency for both G1 and G2. In G2, estimated GWP emissions and energy by fuel type were retrieved from [20], the mix of fuel types was determined by the selected energy use data for each scenario. Finally, the third GWP scenario, G3, used a combination of literature for the California specific energy mix and more thorough accounting of GWP emissions from [20] [22] [21].

Error Assessment

In order to assess the error in a simulated estimate, details of the final machine tool installation were required. The machines studied were Dimension 1200SST produced by Stratasys for FDM, uPrint SE produced by Stratasys for FDM, and Connex350 produced by Objet for Photopolymer-Jetting. The Dimension 1200SST was selected as the target machine, or datum, for subsequent comparison and uncertainty calculation.

Two proxy machines were used to simulate the estimation process, uPrint SE and Connex350. The uPrint SE was expected to be a more accurate proxy given it was also an FDM machine, the Connex350 serves as a proxy via an adjacent technology. Operational scenarios were selected based on 6 weeks of monitoring the frequency and duration of use of all 3 machines in a university job shop in Berkeley, California. Data on the facility HVAC and lighting energy consumption was collected from utility monitoring and added as an additional input to energy consumption. Peripheral components used to run the machines, such as computers, were considered captured in the building usage since these machines support a large number of activities in addition to the target machine.

The environmental impact scenario options are limited to GWP as measured in kilograms of carbon-dioxide equivalent weight for this study. Data sources for energy mix, delivery efficiency, and GWP produced per kilowatt-hour began most broadly with economically correlated emissions and improve in specificity with literature data from national and state-specific sources. EIO data serves for the most basic and broad estimate scenario [19]. The intermediately detailed estimate data comes from the National Research Council [20]. The most detailed accounting of emissions and efficiency comes from a combination of literature, namely the State of California [21], the National Academy of Sciences [20] and a quality study by Hondo [22].

Results

The inclusion of various data sources and energy allocation methods into the prediction scheme provided an informative distribution of energy and global warming potential estimates. Distinct operational phases were present for all three machines. Separation of operational phases was completed by manually selecting transition points in accordance with the machine controller display and checked graphically.

Table 4. Power demand by operation state for Dimension 1200SST Fused Deposition Modeling Machine

Operation State	Average Power (W)	Standard Deviation (W)
Warm Up	685	270*
Idle	243	63
Production	784	26
Standby	162	23

* Distribution for warm-up is multi-modal contributing to a large variance

Power demand for the Dimension 1200SST Fused Deposition Modeling machine clearly shows differing low frequency cycles during different operating phases. The warm up phase has a long period of continuous power demand preceded by a short energy spike and short period of low power demand. The production phase has a low cycle of high energy demand as well as high frequency oscillations with lower amplitude (Figure 1).The anomaly was induced by the loading door being left open for an extended period of time (5 minutes). A short secondary warm-up period is contained within the anomaly. Summary data for each phase indicates the production phase has the highest overall power demand (Figure 1). Idle and standby phases are separated due to 1) idle may transition to production, but standby must transition to warm-up and 2) the differing power demand.

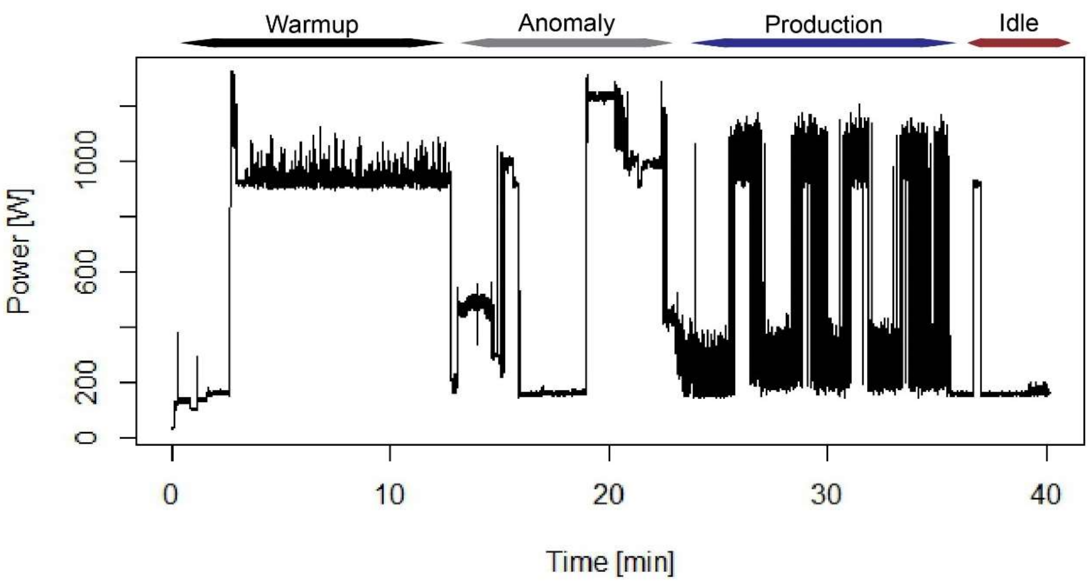

Figure 1. Dimension 1200SST instantaneous power demand from off state with overnight soak and production of a small part

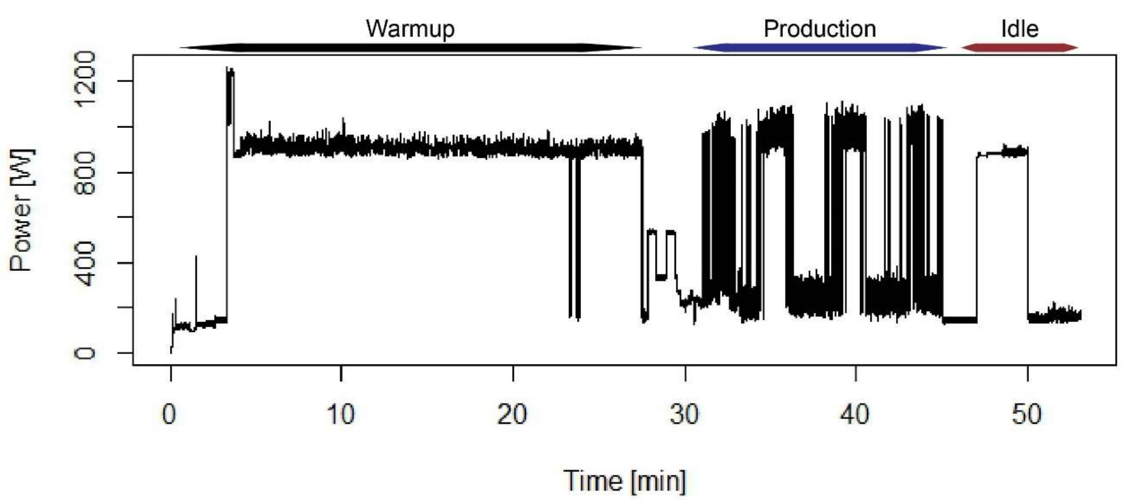

Figure 2. uPrint SE instantaneous power demand from off state with overnight soak and production of a small part [14].

The uPrint SE power demand graph follow very similarly to the Dimension 1200SST with a long warm-up period of continuous power consumption followed by a production phase with a distinct low frequency of high amplitude and higher frequency with lower amplitude Figure 2). Differently than the two FDM machines, the Connex 350 has a constant high power consumption level when in production (Figure 3).

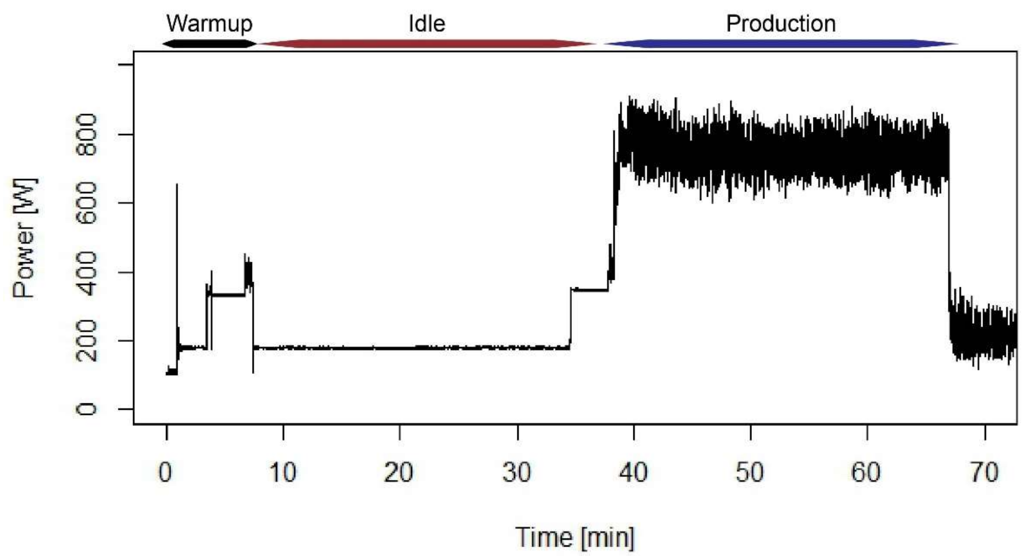

Figure 3. Connex 350 instantaneous power demand from off state with overnight soak and production of a small part [14].

The point estimates generated according to all of the variations in model, data source, and parameter values show a mean that is less than the specific case of the target machine (Figure 4). The mean energy consumption of the target machine was 92 kWh/kg with a standard deviation of 11 kWh/kg. The mean energy consumption of all estimates was 64 kWh/kg with a standard deviation of 15 kWh/kg. Three data sources were used to calculate GWP corresponding to the distribution of energy consumption estimates giving a tri-modal histogram. The majority of GWP estimates were below the target machine mean GWP estimate (Figure 5). The mean GWP of all estimates was 84 kg CO_2-eq/kg part produced, with a standard deviation of 48 kg CO_2-eq/kg part produced. The mean GWP estimate for the target machine was , 120 kg CO_2-eq/kg part produced, with a standard deviation of 14 kg CO_2-eq/kg part produced. The three peaks from all estimates result from the differences in each data set for GWP factors, whereas the target machine has a limited GWP factor range due to its location in Berkeley rather than anywhere in California, or the United States.

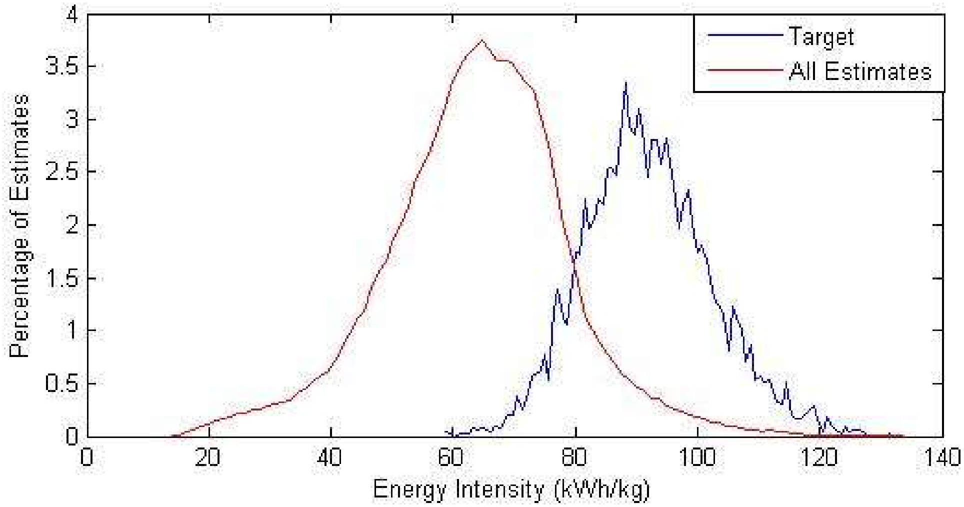

Figure 4. Energy intensity estimates from all considered scenarios and data sources

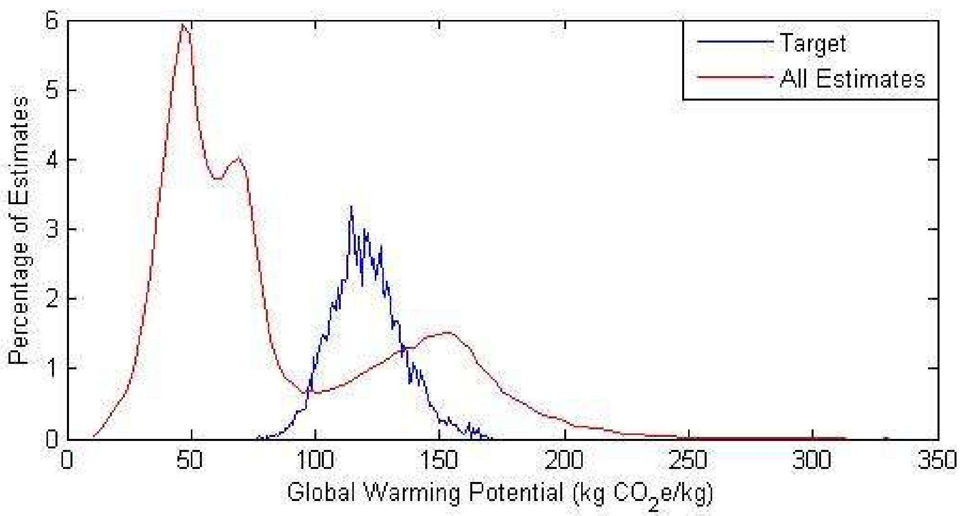

Figure 5. Global Warming Potential estimates from all considered scenarios and data sources

Discussion

The distribution of estimates indicates 1) not every part was produced with an equivalent embodied energy and 2) resource consumption and environmental impact estimates with minimal or missing variance information may be significantly different than the realized quantities.

As mass customization becomes more commonplace with the rise of additive manufacturing, the methodology and results from this study suggest the varying embodied energy of every part may be uniquely identified. In particular, the connection of the duration scaling in Equation (2) to a single part could provide this insight. Interpreting a point estimate of energy usage or global warming potential may have significant and unrealized uncertainty based on the assumptions and decisions of the estimator. This uncertainty is compounded when a point estimate for energy is then used to generate a point estimate for GWP as seen by the mass of estimates below the target machine in Figure 4 and again in Figure 5.

The proposed method included all three types of uncertainty in a LCA in estimating the environmental impact due to energy consumption of a Fused Deposition Modeling machine in a Northern California job-shop. Implicit in the simulation construction was that every set of estimates is given the same weight from an equal number of samples, this suggests that a person chosen at random to complete an estimate is equally likely to construct any of the simulated results. The results suggest that point estimates will tend to underestimate the impacts, and that proxy machines and processes are not necessarily good estimators for energy usage of a new technology. Indication of the potential error due to the use of different data sets–even from very similar machines–is demonstrated, which illustrates the need for this methodology. For example, two of the three datasets used for estimating GWP have a limited range and shift a large portion of the simulated estimates below the target. However, using the most liberal GWP factors from the U.S. national averages, the estimates shift above the target.

The results support the notion that increased collection and clarity of data will continue to improve resource intensity predictions and environmental impact assessments. The use of data from proxy machines or technologies in an estimate may result in either overestimate or underestimate. Whether the estimation is over or under is not necessarily known a priori and dev. The decisions of the researcher in setting up an estimate of resource consumption and account for sub-processes has a significant effect on the outcome of the results. In appropriately assigned distributions may artificially widen or narrow the variance of an estimate. Even though life cycle assessments are intended to enable standardized comparisons, comparative analyses using multiple methods on the same data set are infrequently realized and should be conducted for completeness.

The methodology presented here may be more broadly applicable to measuring and estimating resource intensities and environmental impacts of other additive manufacturing machines. The energy characterization method from [14] and [17] has been shown useful for multiple FDM machines as well as Photopolymer Jetting, and could be useful in other additive technologies. Extension of this work to include material, human health, or other factors is possible with data and models for those factors. The results of this study demonstrate point estimates should be considered with great caution by decision makers and enterprise planning for resource consumption could benefit from estimates with wider ranges.

References

[1] International Standard Organization, ISO 14040: Enmental Management-Life Cycle Assessment Principles and Framework, 1997.

[2] J. Reap, F. Roman, S. Duncan and B. Bras, "A survey of unresolved problems in life cycle assessment," *International Journal of Life Cycle Assessment,* vol. 13, no. 5, pp. 374-388, May 2008.

[3] S. Lloyd and R. Ries, "Characterising, propagating, and analyzing uncertainty in life-cycle anssessment: Asurvey of quantitative approaches," *Journal of Industrial Ecology,* vol. 11, no. 1, pp. 161-179, 2007.

[4] T. McKone and K. Bogen, "Uncertainties in health-risk assessment: an integrated case study based on tetrachloroethylene in california groundwater," *Regulatory Toxicology and Pharmacology,* vol. 15, no. 1, pp. 86-103, 1992.

[5] S. Ross, D. Evans, M. Webber and , "How LCA studies deal with uncertainty," *International Journal of Life Cycle Assessment,* vol. 7, no. 1, pp. 47-52, 2002.

[6] U.S. Environmental Protection Agency, Exposure Factors Handbook: 2011 Edition. Number 3. National Center for Environmental Assessment, September 2011 ed., Washington, D.C.: National Center for Environmental Assessment, 2011.

[7] B. Vigon and A. Jenson, "Life cycle assessment: data quality and databases practitioner survey," *Journal of Cleaner Production,* vol. 3, no. 3, pp. 135-141, 1995.

[8] B. Weidema and S. Wesnaes, "Data quality management for life cycle inventories--anexample of using data quality indicators," *Journal of Cleaner Production,* vol. 4, no. 3, pp. 167-174, 1996.

[9] C. Dujet, E. Benetto and P. Rousseaux, "Integrating fuzzy multicriteria analysis and uncertainty evaluation in life cycle assessment," *Environmental Modeling and Software,* vol. 23, no. 12, pp. 1461-1467, 2008.

[10] S. Lo, H. Ma and S. Lo, "Quantifying and reducing uncertainty in life cycle assessment using the baysian monte carlo method," *Science of the Total Environment,* vol. 340, no. 1-3, pp. 23-33, March 2005.

[11] G. Sonnemann, M. Schuhmacher and F. Castells, "Unceratinty assessment by a monte carlo simulation in a life cycle inventory of electricity produced by a waste incinerator," *Journal of Cleaner Production,* vol. 11, no. 3, pp. 279-292, 2003.

[12] A. E. Bjorklund, "Survey of approaches to improve reliability in LCA," *The International Journal of Life Cycle Assessment,* vol. 7, no. 2, pp. 64-72, 2002.

[13] A. Azapagic, A. Emsley and L. Hamerton, Polymers, the Environment and Sustainable Development, John Wiley & Sons, 2003.

[14] L. M. Clemon, A. Sudradjat, M. Jaquez, A. Krishna, M. Rammah and D. Dornfeld, "Precision and energy usage for additive manufacturing," in *Proceedings for 2013 ASME International Congress and Exhibition*, 2013.

[15] U.S. Energy Information Administration, "Annual Energy Review," 2011.

[16] University of California, Berkeley, "Energy Dashboards," University of California Regents, [Online]. Available: http://sustainability.berkeley.edu/energy-dashboards. [Accessed 16 March 2013].

[17] A. Vijayaraghavan and D. Dornfeld, "Automated energy monitoring of machine tools," *CIRP Annals Manufacturing Technology,* vol. 59, p. 189–201, 2010.

[18] L. M. Clemon, Analysis of Uncertainty in Estimating the Resource Intensities and Impacts of Solid Freeform Fabrication Processes, vol. Masters Thesis, Berkeley, California: University of California, 2013.

[19] L. Lave, H. Matthews and C. Hendrickson, "Environmental life cycle assessment of goods and services: An input-output approach," 2006.

[20] Committee on Health, Other External Costs, Benefits of Energy Production, Board on Enivronmental Studies, Board on Energy, Environmental Systems, and Board on Science,

Economic Policy, "Hidden Costs of Energy: Unpriced Consequences of Energy Production and Use," National Academy Press, 2010.

[21] Air Resources Board, "California greenhouse gas inventory for 2000-2009," Sacramento, California, 2011.

[22] H. Hondo, "Life cycle GHG emission analysis of power generation systems: Japanese case.," *Energy,* vol. 30, no. 11, pp. 2042-2056, August 2005.

Appendix

Table of input values for the hyper-assumed datum case. This table reflects the most complete knowledge of the target machine operating conditions, Dimension 1200SST.

Table 5. Parameter treatments for Dimension 1200SST Fused Deposition Modeling Machine datum case to compare against all other estimates

Datum Case	**Dimension 1200 SST**				
Parameter	**Minimum**	**Maximum**	**Mean**	**Standard Deviation**	**Distribution**
Power demand (W) – operational phase, production and idle are added for total power demand during production					
Warm up	-	-	685	1	Gamma
Idle	-	-	243	27	Gamma
Production	-	-	541	63	Gamma
Standby	-	-	162	23	Gamma
Time Fractions – to compute duty cycle/utilization/uptime of machine					
Warm-up	0.01	0.1	-	-	Uniform
Idle	0	0.5	-	-	Uniform
Production	0.4	0.8	-	-	Uniform
Standby	0.05	0.5	-	-	Uniform
Auxiliaries	0.1	0.8	-	-	Uniform
Machine area (sq-ft)	10	12	-	-	Gamma
Auxiliary area (sq-ft)	16	18	-	-	Gamma
HVAC – as fraction of building HVAC loading					
Building area (sq-ft)	199898	199901	-	-	Uniform
Building power (W)	99000	135000	-	-	Uniform
Effectiveness	0.3	0.5	-	-	Uniform
Lighting – per sq-ft of machine and auxiliary floor space					
Room W/sq-ft	-	-	0.2	0.001	Uniform
Bulb efficiency	0.9	1	-	-	Uniform