COMBINED BUILD–TIME, ENERGY CONSUMPTION AND COST ESTIMATION FOR DIRECT METAL LASER SINTERING

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Abstract

As a single-step process, Additive Manufacturing (AM) affords full measurability with respect to process energy inputs and production cost. However, the parallel character of AM (allowing the contemporaneous production of multiple parts) poses a number of problems for the estimation of resource consumption. A novel combined estimator of build-time, energy consumption and production cost is presented for the EOSINT M270 Direct Metal Laser Sintering system. It is demonstrated that the quantity and variety of parts demanded and the resulting ability to utilize the available machine capacity impact process efficiency, both in energy and in financial terms.

Introduction

The quantification of manufacturing cost informs the decision to adopt additive techniques in commercial applications. A number of cost estimators have been proposed for various additive technology variants (Alexander et al., 1998; Hopkinson and Dickens, 2003; Byun and Lee, 2006; Ruffo et al., 2006b; Wilson, 2006; Munguia, 2009).

Moreover, a precise understanding of the emissions associated with manufacturing processes is essential regarding decision making towards sustainability. The measurement of such emissions forms an important area of research in the field of industrial ecology, where a variety of methods are employed to analyze the interactions between human activity and the environment (Gößling-Reisemann, 2008). Particularly the quantification of carbon emissions, referred to as 'carbon accounting', requires a precise understanding of the energy flows associated with production processes (Vijayaraghavan and Dornfeld, 2010) and the emission characteristics of the local power grid (Jeswiet and Kara, 2008).

No statement on the quality of a manufacturing process selection decision can be made without considering the manufacturing stage. For the private enterprise, the average manufacturing cost, normally measured per unit of output, is central. Considering the wider social implications of energy consumption, manufacturing process energy consumption is also becoming increasingly important (Taylor, 2008).

The supply chains found in modern manufacturing are often complex and long (Foran et al., 2005). Industrial trends towards globalization, concentration on core activities, shorter product lifecycles and the increasing focus on customer needs will add to supply chain complexity (Blecker and Kersten, 2006). The resulting opacity poses a significant barrier to the measurement and minimization of resource consumption in the manufacturing stage of the product life cycle. The single-step nature of additive processes affords full measurability with respect to process energy inputs and production costs. This is especially interesting as additive processes are able to efficiently create complex product geometries (Hague et al., 2004; Rosen, 2007).

The Additive Manufacturing (AM) process allows the contemporaneous production of multiple, potentially unrelated, components. The technology has therefore been described as a ‘parallel’ manufacturing technology (Ruffo et al., 2006b). However, this aspect creates two problems for the modelling and optimization of additive production:

1. To arrive at some summary measure of cost or energy consumption per part, it is necessary to attribute the total cost and energy consumption incurred during each build. In the single product case this can be done by dividing the total cost and energy consumption of the build by the number of parts contained.

2. It has been shown that the degree of capacity utilization affects the resulting metrics of process efficiency (Ruffo et al., 2006b; Ruffo and Hague, 2007; Baumers et al., 2011). Therefore, to be able to claim that a build is performed at minimum cost and energy consumption, the available machine capacity should be fully utilized. In this research, the issue is approached by implementing a packing algorithm that fills the available capacity with parts in an optimized configuration.

A major additive technology variant used to manufacture metal components is Direct Metal Laser Sintering (DMLS), belonging to the category of powder bed fusion processes (ASTM, 2012). This paper analyzes the EOSINT M270 platform (EOS GmbH, 2010), belonging to the class of DMLS technology. DMLS operates as follows: a three-dimensional representation of the product geometry is digitally cut into discrete slices. These slices are then transmitted to the DMLS machine, which recombines them in a layer-by-layer sequence. To this end, the EOSINT M270 selectively scans the surface of a metal powder bed with a 200 W fiber laser, effectively creating a thin, planar slice of solid part geometry. Once the sintering of the layer is complete, a fresh 0.02 mm increment of metal powder (in this case stainless steel) is deposited and the sintering of the next layer commences. This cycle is repeated until the build is complete.

The proposed model of DMLS build-time, energy consumption and cost suggests that average production cost and energy consumption should not be viewed as dependent on production quantity. This notion has been expressed implicitly for the other additive technology variants (Hopkinson and Dickens, 2003). Rather than being determined by production quantity, the current article suggests that the technology user’s ability to fill the available build space is the prime determinant of efficient technology operation. This conforms to the observation that manufacturers will ideally include as many parts as possible in individual builds (Ruffo and Hague, 2007).

Methodology

Build time estimation forms the basis for several AM production cost models in the literature (Alexander et al., 1998; Byun and Lee, 2006; Campbell et al., 2008). Ruffo et al. (2006b) propose an AM costing model viewing the total cost of a build, C_{Build}, as the sum of all direct raw material costs and the indirect costs of operating the machine. The activity based costing technique (Atrill and McLaney, 1999) is a suitable costing method for capital-heavy production processes such as AM. C_{Build} can thus be modeled as:

$$C_{Build} = m_{Material} \times C_{Material} + T_{Build} \times \dot{C}_{Indirect} \quad (1)$$

The direct costs are obtained by multiplying the mass of deposited material ($m_{Material}$) by the cost of the raw material ($C_{Material}$) per kilogram (£/kg, where a $/£ exchange rate of 1.56 is used). The indirect costs are calculated by multiplying the total build time, T_{Build}, by an indirect cost rate, $\dot{C}_{Indirect}$ (£/s). For an estimate of cost per part, C_{Build} is divided by the number of parts contained in the build.

Therefore, this method is only suitable for builds containing multiple instances of the same part. As a premise, this is quite alien to the idea of AM being used to flexibly build different parts in parallel (Ruffo and Hague, 2007). By dividing the cost estimate of the build (C_{Build}) by the number of parts contained in the build, this type of model is also used to describe a relationship between production quantity and average part cost. Where production quantities are not sufficient to fill the available build space, the model assumes that the available capacity remains empty.

However, it has been observed in practice that additive technology users fill the available build space with as many parts as possible (Ruffo and Hague, 2007). Should the demand for parts not be sufficient to fill the workspace, the technology user has the option to sell excess machine capacity to external bidders. If the problem of excess capacity persists it would further be possible to reduce manufacturing cost by switching to an additive platform with a smaller capacity.

For models of manufacturing cost (especially when taking the form of cost functions) it is normally considered necessary that only efficient technology usage is taken into account (Else and Curwen, 1990). Research has shown that some additive systems operate efficiently only where the available capacity is fully utilized (Ruffo et al., 2006b; Ruffo and Hague, 2007; Baumers et al., 2011). However, to be able to claim that the additive process is used at full capacity, it is central that the build is configured with the maximum number of parts in the build. To approach the problem of filling build volumes, workspace packing algorithms have been developed (Wodziak et al., 1994; Nyaluke et al., 1996; Ikonen et al., 1997). For an efficient packing outcome, Hur et al. (2001) suggest using voxel approximations of part geometry, allowing nested configurations of parts.

To solve the issue of efficient technology usage in energy consumption and cost estimation, this research bases the estimator on an automated build volume packing technique. This functionality is designed to arrange parts in the build volume such that the resulting build configuration is optimized. To allow a relatively simple implementation, a number of decisions were made in the design of the algorithm:

- To achieve a dense packing result, the algorithm is based upon rough voxel representations of the analyzed parts (with a resolution of 5 mm). This effectively discretizes the problem of placing irregular and continuous geometries. Figure 1 illustrates the conversion of continuous part geometry into a voxel approximation. To avoid problems of anisotropic material properties occurring in the DMLS process, part rotation is constrained to the vertical axis. Rotation is also limited to discrete 90° steps.

- The parts are inserted into the build volume in a fixed sequence which is predetermined. Further, the algorithm is able to insert a variety of parts. It ensures that at least one instance of each assessed part type is included in the build volume.

- As an evaluation criterion, the algorithm uses a ‘barycentric’ packing heuristic. This means that the algorithm computes the combined center of mass of all parts contained in the build volume. When a further part is inserted, it is moved such that its center of mass is as close as possible to the existing combined center of mass. This produces a dense configuration of parts and also allows for nesting of components.

- In the DMLS process, all parts must be connected to a removable build plate, forming the build volume floor. This is done to prevent part deformation due the heat introduced during the process and to allow heat dissipation into the machine frame. Thus, the algorithm only considers arrangements in which all parts are placed on the substrate, effectively limiting part movement to the X/Y plane.

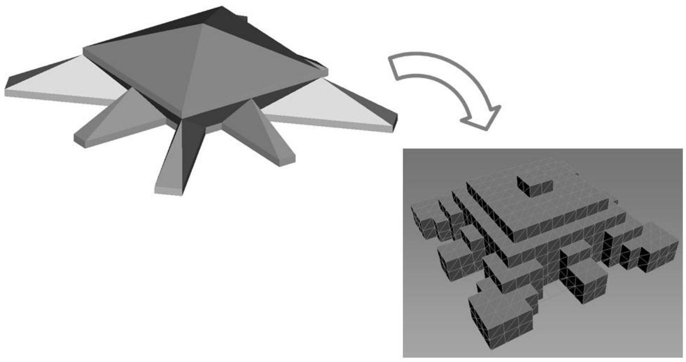

Figure 1: Conversion of a test part into a voxel approximation

After implementing the required build volume packing functionality, the next step in the construction of the combined estimator is to decide on a basket of test parts. The composition of this basket is chosen to be representative of the products commercially manufactured using DMLS and to reflect variation in product size, geometry, and application. The used basket of parts is shown in Figure 2.

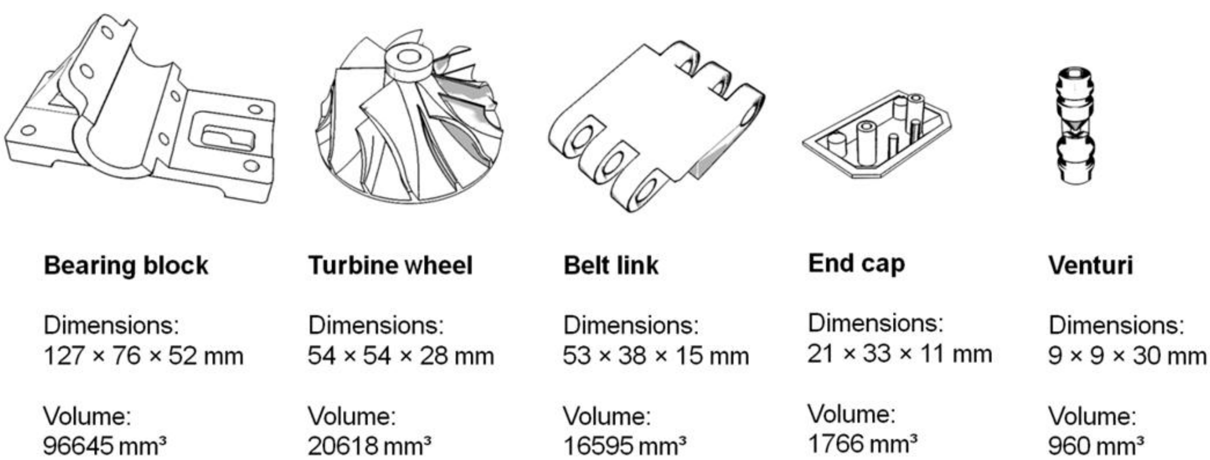

Figure 2: A basket of representative parts

In an attempt to emulate a realistic application of DMLS, the workspace is populated with parts drawn from this basket for a full build experiment. Two further build experiments were performed to validate the model, each holding a single part from the basket. Build progress and process energy consumption were monitored throughout the build experiments with a Yokogawa CW240 digital power meter configured to a time resolution of 1s. Thermal management considerations did not flow into the build configurations.

To generate the build time and energy consumption data required for the combined estimator, a further build experiment was performed and monitored with a higher time resolution (100 ms). In this experiment, a single specifically designed test part was built directly on the build platform. As shown in Figure 3, this test part features a layered design to give an insight into the EOSINT M270's material deposition process.

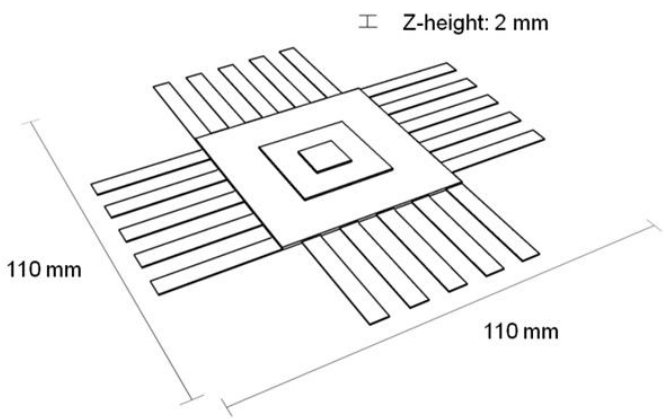

Figure 3: Design of the power monitoring test part

Next to actual process energy consumption, additional energy is consumed for the separation of the parts from the removable build plate. This is done in an ancillary wire erosion process using an Agie Charmilles CUT20 wire eroder. This setup was also power monitored.

Once the build configuration is determined through an execution of the build volume packing algorithm and the data on build speed, energy consumption and production cost have been collected, the combined model can be constructed. In order to do this, the first step is to estimate build time, T_{Build}, which is obtained by combining data from a hierarchy of elements of time consumption:

- fixed time consumption per build operation, T_{Job}, including, for example, machine atmosphere generation and machine warm-up,
- total layer dependent time consumption, obtained by multiplying the fixed time consumption per layer, T_{Layer}, by the total number of build layers l,
- the total build time needed for the deposition of part geometry approximated by the voxels. The triple Σ operator in equation (2) expresses the summation of the time needed to process each voxel, $T_{Voxel\ xyz}$, in a three-dimensional array representing the discretized build configuration:

$$T_{Build} = T_{Job} + \left(T_{Layer} \times l\right) + \sum_{z=1}^{z}\sum_{y=1}^{y}\sum_{x=1}^{x} T_{Voxel\,xyz} \tag{2}$$

No allowance is made for build preparation and machine cleaning. It is felt that the time spent on these activities is difficult to measure and very much at the discretion of the machine operator. It could be argued that these activities take place during the non-operational hours.

Total energy investment, E_{Build}, can be modeled similarly to equation (2). However, a purely time-dependent element of power consumption must be expected in the continuous operation of the AM machine. This is denoted by the energy consumption rate $\dot{E}_{Time}$ (measured in MJ/s), which is multiplied by T_{Build} to estimate total time-dependent energy consumption. Modelling $\dot{E}_{Time}$ as a constant reflects the mean baseline level of energy consumption throughout the build, originating from continuously operating machine components such as cooling fans, pumps, and the control system.

E_{Job} contains all energy consumption attributable to the build job, including energy consumed by the wire erosion process to harvest the parts from the build plate. Analogous to build time estimation, E_{Layer} denotes fixed elements of energy consumption per build and layer, for a total number of layers, l. Further, the geometry-dependent energy consumption is obtained by adding all energy consumption associated with actual material deposition, $E_{Voxel\ xyz}$, throughout the discretized workspace. Please note that $E_{Voxel\ xyz}$ does not contain time-dependent power consumption. The empirical data on $E_{Voxel\ xyz}$ were obtained by monitoring machine energy consumption during the scanning process and then subtracting the energy associated with the energy consumption rate $\dot{E}_{Time}$, ensuring that this element of energy consumption is not counted twice. Thus, E_{Build} can be modeled as follows:

$$E_{Build} = E_{Job} + \left(\dot{E}_{Time} \times T_{Build}\right) + \left(E_{Layer} \times l\right) + \sum_{z=1}^{z}\sum_{y=1}^{y}\sum_{x=1}^{x} E_{Voxel\,xyz} \tag{3}$$

This energy consumption model should not be interpreted as showing how total AM energy consumption can be attributed to individual subunits of the EOSINT M270 platform. The specification was chosen with the goal of implementing a voxel-based energy consumption estimator. Moreover, both the time and energy estimators possess additional information on the real Z-height of the parts contained in the build. This is done to avoid large estimation errors arising from the inclusion of empty layers.

After developing the build time and energy consumption techniques, the next step towards the combined estimator is the construction of an activity-based cost (ABC) estimator of the type devised by Ruffo et al. (2006b). The cost estimate for the build, C_{Build}, is computed from data on the total indirect costs and direct costs incurred. All data used in the costing model are summarized in Table 1. The current research estimates the total indirect cost rate of operating the EOSINT M270 at £26.64 per hour. It is noteworthy that the system incorporates an N_2 generator, hence no protective gas from external sources is needed.

Table 1: Cost model elements (adapted from Ruffo et al. 2006b)

Production overhead			**Utilization**		
Rent, building area cost	4.53	£ / h	Utilization rate	57.04	%
			Annual machine operating hours	5000.00	h
Administration overhead					
Hardware purchase	1670.27	£	**Equipment**		
Software purchase	1670.27	£	AM equipment and wire eroder	8.00	years
Hardware cost/year	334.05	£	Hardware and software	5.00	years
Software cost/year	334.05	£			
Consumables per year	1113.52	£	**Machine costs**		
Total administration overhead	0.31	£ / h	Machine purchase	364406.80	£
			Machine purchase cost per year	45550.85	£
Production labor			Maintenance cost per year	22033.90	£
Technician annual salary	25165.45	£	Machine consumables per year	2542.37	£
Employer contributions	22.00	%	Wire erosion machine purchase	55000.00	£
Total production labor	6.14	£ / h	Total wire erosion costs per year	8165.00	£
			Total machine costs per year	78292.12	£
Total indirect cost per machine hour	**26.64**	**£**			
Direct cost for 17-4 PH powder / kg	**78.81**	**£**	**Total machine costs**	**15.66**	**£ / h**
Direct electricity cost / MJ	**0.018**	**£**			

- December 2010 mean $/£ exchange rate: 1.56

In the proposed model, two direct costs enter the total cost estimate: raw material costs and energy costs. Total raw material costs are calculated by multiplying the total mass w of all parts included in the build (including support structures) with the price per kilogram of the stainless steel 17-4 PH powder, $Price_{Raw\ material}$ (78.81 £/kg). Thus, any raw material losses are ignored. The expenditure for energy enters the model by multiplication of the energy consumption estimate, E_{Build}, with the mean price of electricity for the manufacturing sector in the UK, $Price_{Energy}$, currently around 0.018 £/MJ (according to DECC, 2010). The total cost estimate for the build, C_{Build}, can be expressed as:

$$C_{Build} = \left(\dot{C}_{Indirect} \times T_{Build}\right) + \left(w \times Price_{Raw\ material}\right) + \left(E_{Build} \times Price_{Energy}\right) \tag{4}$$

Results and Discussion

A full-capacity build experiment is configured by executing the build volume packing algorithm. The resulting full build configuration is shown in Figure 4. Of the available 2,025 build volume floor voxels, 92.6% were occupied. A total of 85 parts were inserted, utilizing 19.78% of the used build volume cuboid (225 mm x 225 mm x 52 mm). This value includes the auxiliary structures needed to anchor the overhanging part geometry on the substrate.

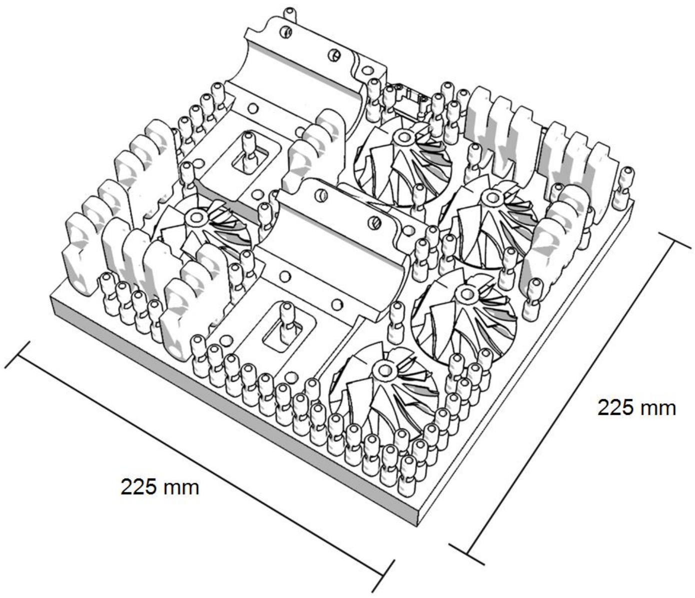

Figure 4: Full build configuration of basket parts

The full build experiment (including the wire erosion process) consumed a total of 1059.56 MJ of energy. Using the cost model specified in equation (4), C_{Build} is estimated at £3,218.87. Individual part cost and energy usage are identified through their share of total product mass (4.167 kg). A summary of the parts produced in the full build and estimates of energy usage and production cost are presented in Figure 5:

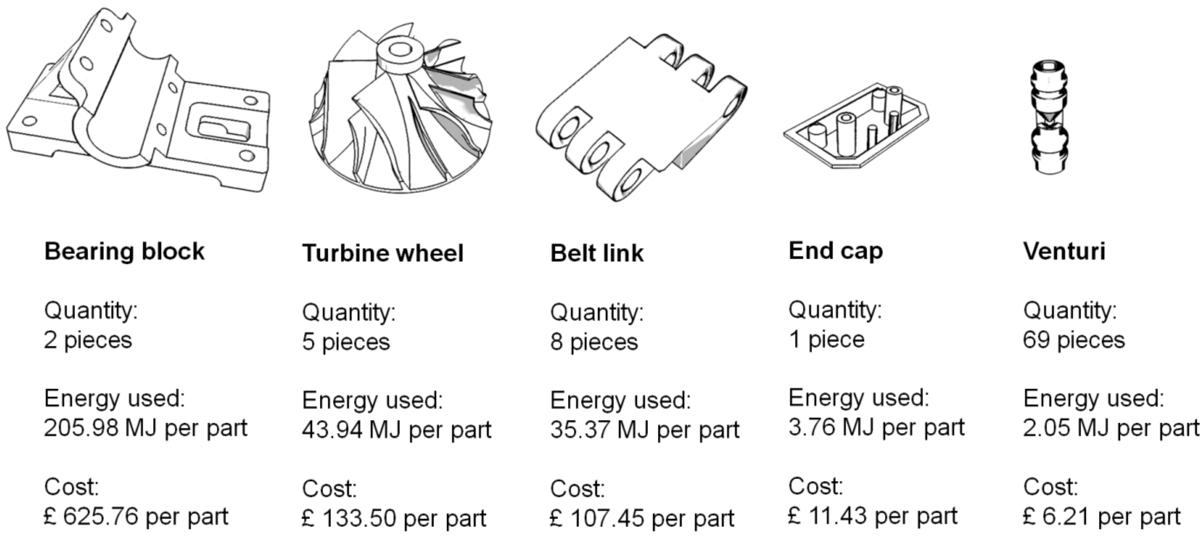

Figure 5: Estimates of energy consumption and production cost per part

The final specifications of the time and energy estimators, equations (2) and (3), are obtained from a least squares regression of the time and energy consumption data recorded during the experiment containing the layered power monitoring test part, as shown in Figure 3.

The obtained parameters α_{Time} (10.82 s) and α_{Energy} (0.008 MJ) are multiplied by the number of layers in the build l in order to obtain layer dependent time and energy consumption. The parameters expressing the time and energy attributable to the scanning of 1 mm² during the build, β_{Time} (0.0125 s) and β_{Energy} (0.000013 MJ), are then used in conjunction with the layer thickness lt (0.02 mm) and a measure of occupancy of each voxel to calculate total time and energy consumption per voxel, $T_{Voxel\,xyz}$ and $E_{Voxel\,xyz}$. The rate of occupancy RO_i in each voxel is modeled as the ratio of the volume of part i occupying this voxel (VP_i) and the volume of the voxel approximation for part i (VA_i):

$$RO_i = \frac{VP_i}{VA_i} \tag{5}$$

Thus, for each (5 mm)³ voxel in the position xyz holding 250 (= 5 mm / lt) layers and containing part i, the build time and energy consumption can be approximated:

$$T_{Voxel\,xyz} = \beta_{Time} \times 5^2 \times \frac{5}{lt} \times RO_i \tag{6}$$

$$E_{Voxel\,xyz} = \beta_{Energy} \times 5^2 \times \frac{5}{lt} \times RO_i \tag{7}$$

This is combined with an estimated fixed time and energy consumption for machine start-up T_{Job} (63 s) and E_{Job} (142.58 MJ, including wire erosion). The start up process is very rapid on this system as no warm up is required and the build chamber is continuously flooded with N_2 during build activity. Time dependent power consumption is obtained by multiplying the base line energy consumption rate $\dot{E}_{Time}$ (0.0015 MJ per s) with T_{Build}. Thus, the estimates of T_{Build} and E_{Build} are obtained as follows:

$$T_{Build} = T_{Job} + (\alpha_{Time} \times l) + \sum_{z=1}^{z} \sum_{y=1}^{y} \sum_{x=1}^{x} T_{Voxel\,xyz} \tag{8}$$

$$E_{Build} = E_{Job} + (\dot{E}_{Time} \times T_{Build}) + \left(\alpha_{Energy} \times l\right) + \sum_{z=1}^{z} \sum_{y=1}^{y} \sum_{x=1}^{x} E_{Voxel\,xyz} \tag{9}$$

The time and energy consumption model specified in equations (8) and (9) is experimentally validated. This is done by comparing the calculated estimates to the measured time and energy consumption during the three build experiments containing parts from the representative basket (Figure 2). Validation is performed for the full build at maximum machine capacity (shown in Figure 4) and two single part builds, the bearing block and the turbine wheel.

The results of the validation experiments and the corresponding estimates of T_{Build} and E_{Build} are presented in Table 2. Note that the validation does not include the energy consumed by the ancillary wire erosion process. It should also be mentioned that some of the venturi parts had an incorrect orientation during the build, which led to build failure for the affected parts in the final stages of the full build. However, this was deemed to have had a negligible effect on the presented results.

Table 2: Confronting the estimates with experimental results

Experiment	Time consumed	Model estimate T_{Build}	Error	Energy usage	Model estimate E_{Build}	Error
Full Build experiment	388031 s	354806 s	-8.56 %	917.10 MJ	879.93 MJ	-4.05 %
Single Bearing block	93302 s	92338 s	-1.03 %	215.48 MJ	223.13 MJ	3.55 %
Single Turbine wheel	31224 s	28504 s	-8.71 %	72.73 MJ	66.80 MJ	-8.15 %

The observed errors are likely to originate from the use of an idealized test part (Figure 3) in the experiment that provided the data. Compared to other build time estimators (Campbell et al. 2008; Munguia 2009; Ruffo et al. 2006a; Wilson 2006) the errors reported in Table 2 indicate that the developed time estimation functionality performs robustly.

This research thus demonstrates that the impacts of the fixed process elements in the DMLS process, which may be job dependent (such as machine start-up) or layer dependent (such as powder re-coating), are amortized over the number of parts contained in the build. This has been previously suggested by Baumers et al (2011) for energy consumption.

The presented technique appears appropriate for additive processes as it can be used to estimate specific energy consumption and production cost for various build configurations with multiple types of parts. To test the effect of various build compositions, eight different configurations with varying degrees of capacity utilization were estimated. The results for process energy consumption range from 1.96 MJ/cm³ to 3.61 MJ/cm³. Assuming a material density of 7.80 g/cm³, this corresponds to specific energy consumption ranging from 251.28 MJ/kg to 462.82 MJ/kg. This is slightly higher than reported in previous research, ranging from 241 MJ/kg to 339 MJ/kg (Baumers et al., 2011). This difference is likely to originate from the inclusion of the energy consumed by the wire erosion process. In terms of production cost, the eight build configurations led to results ranging from 5.71 £/cm³ to 7.44 £/cm³.

The full build configuration shown in Figure 4 resulted in the lowest estimated energy consumption and production cost on the EOSINT M270 (1.96 MJ/cm³ and 5.71 £/cm³). This underlines the statement made in the introduction that for cost and energy consumption metrics to reflect efficient machine operation it is important to consider full capacity utilization. The results thus show that the configuration with the highest packing density is likely to lead to the most efficient build. This points to the conclusion that the user's ability to fully utilize the available build space is an important determinant of DMLS cost and energy consumption.

Conclusions

This research demonstrates the construction of a combined estimator of build-time, energy consumption and cost for parallel additive techniques such as DMLS which reflects technically efficient machine operation. The application of this methodology shows that the cost and energy consumption of the DMLS process are determined by the user's ability to fill the available build space. Further, the proposed method can be used to estimate the production of own designs in build volumes that are populated (where necessary) with parts drawn from a representative basket.

The developed methodology has been applied to DMLS, which is a laser-based additive platform employing a powder bed. While the results are likely to be extensible to later generations of DMLS systems (such as the EOSINT M280), it is unclear whether they are applicable to other additive processes. These could be platforms operating with a powder bed (for example, Electron Beam Melting) or those with an entirely different operating principle (for example, Fused Deposition Modelling). Further research is needed in this area. Moreover, the model described in this paper is limited to so called 'well structured' costs of manufacturing (Son, 1991). Ill structured costs arising from factors such as build failure, machine idleness and inventory expenses are ignored.

References

1. Alexander, P., Allen, S., and Dutta, D., 1998. Part orientation and build cost determination in layered manufacturing. *Computer-Aided Design*, 30 (5), pp.343-356.

2. ASTM, 2012. *Standard F2792 - 12a, 2012, Standard Terminology for Additive Manufacturing Technologies*. ASTM International, West Conshohocken, PA, 2003, DOI: 10.1520/C0033-03, www.astm.org.

3. Atrill, P., and McLaney, E., 1999. *Management Accounting for Decision Makers*. 2nd ed. London: Prentice Hall Europe.

4. Baumers, M., Tuck, C., Wildman, R., Ashcroft, I., and Hague, R., 2011c. Energy inputs to additive manufacturing: does capacity utilization matter? *Proceedings of the Solid Freeform Fabrication (SFF) Symposium*. The University of Texas at Austin, 2011.

5. Blecker and Kersten, 2006. Preface. In*: Complexity Management in Supply Chains*, Blecker and Kersten (Eds.). Berlin: Erich Schmidt Verlag GmbH & Co.

6. Byun, H., Lee, K. H., 2006. Determination of the optimal build direction for different rapid prototyping processes using multi-criterion decision making. *Robotics and Computer-Integrated Manufacturing*, 22 (1), pp.69-80.

7. Campbell, I., Combrinck, J., De Beer, D., and Barnard, L., 2008. Stereolithography build time estimation based on volumetric calculations. *Rapid Protoyping Journal*, 14 (5), pp.271-279.

8. DECC, 2010. UK *climate change sustainable development indicator: 2008 greenhouse gas emissions, final figures*. [Online]. Available from: http://www.decc.gov.uk/en/content/cms/statistics/climate_change/gg_emissions/uk_emissions/uk_emissions.aspx [Accessed: 01.07.2010].

9. Else, P., and Curwen, P., 1990. *Principles of Microeconomics.* London: Unwin-Hyman.

10. EOS GmbH. *Corporate website*, 2010. [Online]. Available from: http://www.eos.info/en/products.html [Accessed: 24.09.2010].

11. Foran, B., Lenzen, M., Dey, C., and Bilek, M., 2005. Integrating sustainable chain management with triple bottom line accounting. *Ecological Economics*, 52 (2), pp.143-157.

12. Gößling-Reisemann, S., 2008. What Is Resource Consumption and How Can It Be Measured? Theoretical Considerations. *Journal of Industrial Ecology*, 12 (1), pp.10-25.

13. Hague R., Mansour, S., and Saleh, N., 2004. Material and design considerations for rapid manufacturing. *International Journal of Production Research*, 42 (22), pp.4691-4708.

14. Hopkinson, N., and Dickens, P., 2003. Analysis of rapid manufacturing - using layer manufacturing processes for production. *Proceedings of the Institution of Mechanical Engineers, Part C: Journal of Mechanical Engineering Science.* 217 (C1), pp.31-39.

15. Hur, S., Choi, K., Lee, S., Chang, P., 2001. Determination of fabricating orientation and packing in SLS process. *Journal of Materials Processing Technology*, 112 (1), pp.236-243.

16. Ikonen, I., Biles, W. E., Kumar, A., Ragade, R. K., Wissel, J. C., 1997. A Genetic Algorithm for Packing Three-Dimensional Non-Convex Objects Having Cavities and Holes. *Proceedings of the 7th International FAIM Conference*.

17. Jeswiet, J., and Kara, S., 2008. Carbon emissions and CESTM in manufacturing. *CIRP Annals – Manufacturing Technology*, 57, pp.17-20.

18. Munguia, F. J., 2009. RMADS: *Development of a concurrent Rapid Manufacturing Advice System*. Ph.D. thesis, Universitat Politecnica de Catalunya, Barcelona, Spain.

19. Nyaluke, A., Nasser, B., Leep, H. R., Parsaei, H. R., 1996. Rapid prototyping work space optimization. *Computers ind. Engng*. 31 (1/2), pp.103-106.

20. Rosen, D. W., 2007. Computer-Aided Design for Additive Manufacturing of Cellular Structures. *Computer-Aided Design & Applications*, 4(5), pp.585-594.

21. Ruffo, M., and Hague, R., 2007. Cost estimation for rapid manufacturing – simultaneous production of mixed components using laser sintering. *Proceedings of IMech E Part B: Journal of Engineering Manufacture*, 221 (11), pp.1585-1591.

22. Ruffo, M., Tuck, C., and Hague, R., 2006a. Empirical laser sintering time estimator for Duraform PA. *International Journal of Production Research*, 44 (23), pp.5131-5146.

23. Ruffo, M., Tuck, C., and Hague, R., 2006b. Cost estimation for rapid manufacturing – laser sintering production for low to medium volumes. *Proceedings of IMechE Part B: Journal of Engineering Manufacture*, 220 (9), pp.1417-1427.

24. Son, Y. K., 1991. A cost estimation model for advanced manufacturing systems. *International Journal of Production Research*, 29(3), pp.441-452.

25. Taylor, P., 2008. [Online] *Energy Technology Perspectives 2008 – Scenarios and Strategies to 2050.* IEEJ Workshop, Tokyo, 7 July 2008. Available from: http://www.iea.org/speech/2008/taylor_etp2008.pdf [Accessed: 15.08.2011].

26. Vijayaraghavan, A., Dornfeld, D., 2010. Automated energy monitoring of machine tools. *CIRP Annals – Manufacturing Technology*. 59 (1), pp.21-24.

27. Wilson, J. O., 2006. *Selection for rapid manufacturing under epistemic uncertainty*. Master's thesis. Georgia Institute of Technology, Atlanta, USA.

28. Wodziak, J. R., Fadel, G. M., Kirschman, C., 1994. *A genetic algorithm for optimizing multiple part placement to reduce build time*. Proceedings of the Fifth International Conference on Rapid Prototyping, pp.201-210.