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## Effect of build parameters on processing efficiency and material performance in fused deposition modelling

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### Abstract

Advances in additive manufacturing have resulted in significant growth of such materials, including the medical sector. It is particularly applicable to manufacture of prosthetics and implants, where design freedoms and complex geometries afforded by additive manufacturing are especially suited to such products. With this growth it is timely to consider approaches to optimization for both efficiency and performance. In this work a design of experiments approach was used to quantify the effects of build parameters on performance and efficiency outputs. This approach could prove invaluable to designers for both cost and performance optimization, applicable to both prototype and part production.

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**Keywords:** fused deposition modelling; design of experiments; process optimisation

### 1. Introduction

Additive manufacturing (AM) describes a process where parts are manufactured layer by layer in an additive process [1]. Originally used in the production of complex geometry prototypes (RP), advances in the technology now make AM applicable to rapid manufacturing (RM) [2]. Although AM is unable to compete with the short cycle times and lower capital costs of more traditional processes such as injection moulding, this is compensated by the design freedoms allowed by the ability of AM processes to produce complex geometries, as well as reduced tooling costs and lead times [3].

There are various techniques classed within AM, the earliest known being stereolithography. There are also powder bed fusion processes such as selective laser sintering. The subject of this work is a material extrusion based technique called fused deposition modelling, FDM [4], which is one of the most commonly used AM techniques [5]. FDM was introduced in 1992 by American company Stratasys [6]. FDM was initially used to create conceptual models to aid product design however process and material developments have allowed FDM to diversify from RP into RM.

It is clear from the scientific literature that processing parameters in FDM affect the characteristics of manufactured products [7-13]. The most considerable challenge for FDM in RM is the selection of build parameters for optimization of performance in conjunction with cost minimization [14].

#### Nomenclature

|     |                            |
|-----|----------------------------|
| AM  | additive manufacturing     |
| FDM | fused deposition modelling |
| PLA | polylactic acid            |
| RM  | rapid manufacturing        |
| RP  | rapid prototyping          |
| SO  | slice orientation          |

However the energy consumption in AM processes remains relatively unexplored. However there are some recent studies, for example Balogun et al, 2014 [13].

Medical applications of AM are expanding rapidly. Within the medical sector AM can be used in production of prosthetics and implants, models and tissue fabrication [15]. The greatest of advantage of AM in the medical sector is the design freedoms afforded in customization of products and

equipment [15]. Other benefits include increased cost efficiency [16] and enhanced productivity [17]. The ability to produce complex geometries is especially advantageous in the manufacture of prosthetics and implants, where medical scans can be translated into the .stl files required by AM machinery [18].

As AM continues to grow within and into new sectors, it is timely to consider approaches to analyse the effects of the machine build parameters on the final properties of built parts, as well as on the effects of efficiency factors such as material usage and build times. This work presents a systematic approach to quantifying relevant build parameters to measured material outputs and efficiency factors, and demonstrates how such studies can be used in part and process optimization, depending on the product requirements.

## 2. Experimental Procedure

### 2.1 Materials and equipment

Parts were manufactured from PLA filament of diameter 1.75 mm, specifically produced for the FDM machine used in this work, a Makerbot Replicator 2. Default settings of extrusion temperature and speed were used as recommended by the manufacturer. The specimens were designed for conformity with ISO 527-2, for tensile testing of plastics.

### 2.2 Design of experiments

A full factorial DoE was utilized so as to collate data in a controlled way. The FDM machine inputs (parameters) and their associated variables are listed in Table 1. The SO refers to the orientation at which the object is built, and is depicted for tensile testing specimens in Figure 1. The infill level represents the density of the internal structure of the part, a 100 % infill resulting in a completely solid part. Infills under 100 % are built in regular hexagonal patterns, the size of which decrease proportionately with higher infill. A shell is a border that is printed for each layer. The machinery prints a minimum of one shell per layer. The layer height defines the thickness of each printed layer.

Table 1. Full factorial design of experiments

| Experiment no. | SO    | Infill (%) | No. of shells | Layer height (mm) |
|----------------|-------|------------|---------------|-------------------|
| 1              | Front | 60         | 1             | 0.15              |
| 2              | Front | 60         | 1             | 0.4               |
| 3              | Front | 60         | 4             | 0.15              |
| 4              | Front | 60         | 4             | 0.4               |
| 5              | Front | 100        | 1             | 0.15              |
| 6              | Front | 100        | 1             | 0.4               |
| 7              | Front | 100        | 4             | 0.15              |
| 8              | Front | 100        | 4             | 0.4               |
| 9              | Side  | 60         | 1             | 0.15              |
| 10             | Side  | 60         | 1             | 0.4               |
| 11             | Side  | 60         | 4             | 0.15              |
| 12             | Side  | 60         | 4             | 0.4               |
| 13             | Side  | 100        | 1             | 0.15              |
| 14             | Side  | 100        | 1             | 0.4               |
| 15             | Side  | 100        | 4             | 0.15              |
| 16             | Side  | 100        | 4             | 0.4               |

The measured outputs were split into two categories; efficiency outputs and performance outputs, which are listed in Table 2.

Table 2. Measured outputs of FDM parts

| Efficiency         | Performance      |
|--------------------|------------------|
| Build time         | Tensile strength |
| Energy consumption | Young's modulus  |
| Part weight        |                  |
| Scrap weight       |                  |

### 2.3 Testing and analysis

The tensile tests were performed on a Zwick Roell Z010 tensometer, and data gathered with TestExpert II 3.6 software. The tensometer was fitted with a 10 kN load cell, of accuracy 0.08 %. For each experiment (Table 1), 10 specimens were produced, 160 in total. The outputs (Table 2) were analyzed using Minitab 16. Main effects plots were used to assess the relative effects of each parameter, and Pareto plots used to quantify which parameters (and combinations of parameters) significantly affected the outputs at 95 % confidence level. Contour plots were generated for multi-objective analysis.

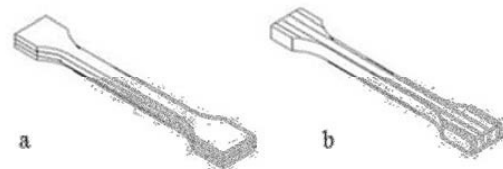


Fig. 1. (a) front SO; (b) side SO.

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