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Smart Additive Manufacturing – an AM Intelligent Platform

D1.4 State of the Art Overview

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CHANGE HISTORY

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0.1	2021-03-15	First draft version.	All
0.2	2021-07-01	Added section on Machine Learning Solutions	2.2.1
1.0	2021-08	First version.	All
2.0	2022-07	Added section on build orientation. Added section on part identification (using machine learning as well as image processing)	4 & 5

CONTENT

1 Introduction

1.1 Goal of this Document

This document presents a structured overview of the state of the art relevant to the SAMUEL project. The scope of this review is dictated by our Use Cases. Listed are products and services currently available which relates to the project, and available technology and research which could be leveraged. For a wider state of the art, included an overview of the AM industry, please refer to the current SAMUEL FPP Annex (Section 2.3.1).

2 Build Time Estimation

Directly related to one of Belgium's Use Case, build time estimation is also a crucial part of the quoting process, also addressed by a Canadian Use Case. As such, results on this subject are of interest to the whole SAMUEL consortium.

Calculation of AM build time is an important step in the AM workflow. First, manufacturers need to know how long a build will take in order to properly plan their production. Secondly, time spent on a machine must be accounted in the cost of a part (or an order).

2.1 Currently Available Solutions

Machine manufacturers are well placed to offer a build time estimation solution. They know the inner workings of the AM equipment they provide, the parameters the user can control and their impact on the build time, and they also control the slicing and path creation strategy. However, by their position, these solutions are limited to a specific equipment manufacturer, each with their own approaches, solutions, strategies and limitations.

Build preparation software can also provide build time estimation.

2.1.1 Autodesk Netfabb

Autodesk's Netfabb software offers build time estimation functionalities as part of their *Advanced Toolpathing Utility* [1] strictly for Powder Bed Fusion AM Process. This utility exposes JavaScript functions [2] that the user may leverage to generate toolpaths and calculate tool travel times. This feature is not available through the software UI. The software does not leverage or consider historical data from the Manufacturer.

2.1.2 3D Systems's 3DXpert

3DSystems's 3DXpert offers build time estimate functionality in its standard version, as part of the *Estimate* tool. The user must enter his machine characteristics, namely part and support printing rate (mm^2/s) and time between layers [3]. The software does not leverage or consider historical data from the Manufacturer.

2.1.3 Materialise's Magics

Materialise's Magics also offers a build time estimate function [4]. The tool is based on "Learning Platform" where the user provides completed, reference platforms, specifies the machine used, laser power and enters the real build time of each of those platforms. Magics then can estimate build times based on those reference platforms.

2.2 Applicable Technology

We can break down built time estimation strategies in three main groups: Volumetric analysis, Path analysis and Machine Learning solutions.

In a volumetric analysis, the surface of the slices (of both parts and supports) are measured, then multiplied by the printing rate of the machine (which may be different between parts and supports). Time is also added to account for the process done between each layer.

Path based analysis works in a similar fashion as in the machining industry. Nozzle or laser advance speed is calculated along the path generated by the slicer and cumulated. Again, time is also added to account for the process done between each layer.

Machine-Learning approaches lean on historical data. These tools leverage the data gathered by the user's production and use it to make build time estimation of new parts and platform configurations.

2.2.1 Machine Learning Solutions

The studies in the literature that propose to use learning methods for build time estimation (BTE) can broadly be categorized into the classical machine learning (ML) and the new deep learning (DL) methods. Artificial Neural Network (ANN) is the most common ML method that was used for BTE. For instance, in [5] an ANN was trained using a relatively small set of objects, and z-height, part volume, and bounding-box volume as input features of the network. The obtained results demonstrated that an ANN can provide better results than the physics-based methods which use predetermined functions for BTE. However, the authors highlighted that one of the important drawbacks of this approach is the difficulty of reproducing the same results under different conditions since several different factors, e.g. training data, network configuration, normalization strategy, etc., might have a dramatic impact on the ANN performance.

An ANN was also used in [6] for BTE and a larger set of input features, eight different build time driving factors, were given to the network in order to find the mapping between these features and the objects' build times. The eight driving factors were: 1) object volume/object layer thickness, 2) object height/object layer thickness, 3) object's total length of the layers' contour to be deposited, 4) number of repositioning movements for object, 5) support volume/support layer thickness, 6) support height/support layer thickness, 7) support's total length of the layers' contour to be deposited and, 8) number of repositioning movements for support. The authors reported that the approach showed relatively good performance, with error rates ranging between 6% and 20%, on a limited set of 6 test cases specially selected as difficult to predict build time.

Thanks to the recent advancements of the DL methods, it is possible to properly exploit the rich and complex AM datasets which contain different types of measurements like 3D models, build parameters, printing instructions, process monitoring data, and quality control and post-processing data. Currently, meshes and CAD models are used to represent the 3D model that has to be manufactured. The printing instructions typically consist of a set of 2D vectors specifying for each layer where material has to be scanned or deposited. The type of data collected during monitoring of the manufacturing process, depends on the sensors being used, e.g. images are captured to monitor the printing process layer by layer. These images can be thermal images or visual images.

The data collected during post-processing, quality control and inspections can consist of 2D images, 3D object measurements or CT scans.

Analysis of the image data collected during the different phases of an AM process can be performed using deep convolutional neural networks (CNNs). CNNs are a family of DL algorithms, suitable for encoding image data and yielded remarkable results in image classification [7], object detection [8] and image segmentation [9]. Design and implementation of the deep CNNs can be performed by using multiple open-source software packages, specifically designed and optimized for deep learning [10] [11] [12].

A deep variational autoencoder network for voxelized geometry was employed in [13] in order to learn a low-dimensional representation of the high-dimensional part designs. The learned low-dimensional representation was then used to train three separate deep neural networks for predicting part mass, mass of the support material and build time. However, the obtained results were not very encouraging due to the limited prediction accuracy. Recently, a 3D convolutional neural network (CNN) was used in [14] to map an input of voxel-based 3D geometry to an output value as estimation of build time and the performance of the network was compared with linear regression model as baseline. The obtained results showed that 3D CNN was more accurate than the baseline method.

Another way for analysing voxel data is to create a voxel representation of the 3D model, then process it as a 3D image. However, this incurs tradeoffs between voxel resolution, performance and precision. Also, it negates the model's arbitrary level of detail: sub-voxel size features can be important e.g. to predict build times, to suggest build parameters, to calculate an ideal build orientation, or to generate sup-port. Alternatively, 3D objects can be represented by images, e.g.: images created from multiple points of view. Or images from different sensors, for example: a depth field camera and a color image. These images can then be used as input for a CNN [15] [16].

Besides the representations of 3D objects similar to images, 3D objects can be represented by a point cloud, descriptors, surface parameterizations, graphs, meshes, octrees, etc. For each of these examples at least one specialized, deep learning algorithm has been developed [15] [17] [18] [19].

The challenge is to find a technology that is broadly applicable or to map which data representations fits best with the different applications in machine learning for additive manufacturing. Improved voxel-like solutions using a fine but sparse voxel grid, like OctTrees, seem especially promising, but have the disadvantage of not being readily supported in the common matrix-based software frameworks [20]. Point cloud-based solutions do not have that problem, but are limited by the loss of connectivity and volume information [21] [22].

Surface based solutions do exist, though they rely on local surface parameterizations, they basically learning local surface features [23]. These have shown good results in surface-centered applications, such as CFD prediction or surface labelling [24]. Other mesh-based techniques are similar to point clouds based methods but use triangles instead [18].

3 Cost Estimation

3.1 Currently Available Solutions

There are tools available to help the quoting process in the traditional manufacturing market. Products like aPriori [25] and LeanCOST [26] create a rich cost model by integrating design data (from the part's CAD model) and a wide range of manufacturing data.

Some build preparation software provides cost estimation capabilities. For example, 3DSystems's 3DXpert can calculate costs based on material consumption and machine time [3]. These software however can only estimate costs related to the print process, and may miss auxiliary costs needed for a complete quote (post-processing costs are a good example).

There are some AM-dedicated products which are starting to emerge. CASTOR [27], by the start-up Castor Technologies Ltd, is an automated part screening software that informs manufacturers when it is beneficial to use 3D printing instead of traditional manufacturing methods. The proprietary software conducts a technical and economic analysis for CAD files of full assemblies or individual parts resulting in a report determining each part's 3D printability. Castor provides an estimation of the cost and lead time for 3D printing in comparison of other traditional manufacturing methods such as molding or machining. Although this might be interesting at an early stage to select a manufacturing process, the accuracy of their costing application might not be sufficient for a manufacturer specializing in AM who needs to compete on price and therefore provide an accurate cost prediction.

Etteplan launched the free, online cost estimation tool AMOTool [28]. The estimation provided is not based on the 3D model (which is not uploaded) but rather on data inputted manually by the user (part height, part volume, machine type, material, etc…) The tool can then offer a cost estimation, but also provide the user with a cost reduction matrix. AMOTool is suited for managers and engineers to make product development decisions and to understand if additive manufacturing is a viable option for production. Like CASTOR, it does not target AM Manufacturers.

Some 3D Printing services offer an "Instant Quote" feature to their users. i.materialise [29] and Xometry [30] are some of the platforms which offer such feature. The Xometry *Instant Quote Engine* is powered by neural net-based machine learning [30], and can provide quotes not only for AM techniques, but for traditional manufacturing too.

All this being said, in the context of small to medium companies, the truth is that the aforementioned solutions are still inadequate, inefficient or too expensive. Therefore, Microsoft Excel is still the go-to solution for most of these companies.

3.2 Applicable Technology

Build time estimation being an major part in cost estimation, applicable technology detailed in section 2.2 also apply in this context.

Going further than build estimation, other values are needed to estimate costs. A novative way of quickly finding relevant and useful values is to search in its own organisation production history and find previously produced similar parts. The estimated values from those similar parts can, if not taken directly as-is, provide the estimator with a baseline instead of starting from nothing.

Shape-based search here therefore becomes a powerful tool: Once geometrically-similar parts are found in the organisation's production history, documents and estimated values related to those parts can be easily retrieved.

4 Build Preparation

Build preparation is a necessary step in the additive manufacturing process. Parts must be properly placed, oriented and anchored on the build platform on order to yield not only a successful build, but also an efficient one.

4.1 Currently Available Solutions

Materialise is currently market leader in the 3D-printing market, with more than 90% of AM service bureaus are using Materialise Magics for data preparation of AM builds. As mentioned in section 2.1, other software options are available.

With Materialise Magics a user can prepare a build platform. Typically AM machines work in batch, all parts that will be printed in one batch are positioned on a “build platform”. After the 3D-positioning of parts, ‘Build Processor’ prepares the build job, i.e. computes the actual input to the machine. Typically this is done in two steps. First of all the 3D-parts need to be sliced, i.e. computing the cross sections between subsequent horizontal planes and the geometries. The result of a single cross section between a horizontal plane and the build is called a ‘layer’. After this step, for all layers the toolpath needs to be computed, i.e. the path that the main machine actuator (typically laser that is deflected by two scanner mirrors) needs to follow. Everywhere this actuator deposits energy, the raw material (e.g. powder) is transformed into solid material. The toolpath is subsequently used a input for the Materialise Control Platform (MCP), which translates the path into physical data for the machine actuators. During the building process, MCP also monitors the process by reading values from the available sensors in the machine. One of the key advantages of MCP here is the use of fast and configurable electronics, which allow the user to monitor data fast and flexible. Most AM machines are equipped with sensor systems to monitor the build process, and a large amount of data is generated for every build. For instance currently most metal machines take images after scanning and after recoating a new layer. In the Materialise MCP, the user can define what data is captured and stored. The newest product of the tool chain ‘Materialise Inspector’, then helps the user in the interpretation of the data from the build process. Inspector can process data from different machines and can already compare this data with the slice files. However, there is much more information in the huge amount of data that is captured and stored. The next logical step is the extraction of information and learning from that data, using Data Mining and Machine Learning.

One important aspect that will be focused upon within this project is handling the orientation of a part within the build. The orientation has quite an impact on several aspects of the part, the most important being the quality, the build time and the price. At the beginning of the project, the orientation was mainly determined by the operator. The complexity of the requirements did not allow for a one-size-fits-all automatic solution. The reasons to select a specific orientation could be:

- To obtain an accuracy or mechanical properties in a specific direction. An AM part, especially in FDM, displays anisotropic behaviour, in mechanical properties as well as in accuracy. So the user might want to choose an orientation in order to obtain a specific accuracy or strength in a certain direction. This occurs quite often. This is obviously not so easy to automate.

- The main reason to change the orientation of a part however is cost reduction. For individual parts, there are not so many ways to reduce the cost of a build:
    - Reduce the amount of support material.
    - Reduce the individual build time.
    - Reduce the overall build time by combining (as many as possible) parts in one build.

  A combination of all the above will probably lead to a maximal cost reduction but this again depends on the circumstances. In any case, an effective build time estimation (individual or collective) is missing from the state-of-the-art to perform a typically iterative optimisation. Currently, an optimisation is possible towards specific *contributing factors* to the cost:
    - Z-height
    - XY-projected area
    - Support surface area

4.2 Applicable Technology

At first sight, the problems to be solved can be reduced to a standard optimisation problem. However, the often conflicting requirements make it quite difficult to find a representative target function. The goal is to use weighted optimisation in order to allow the user to define a compromise in order to get to a case dependent optimal result. Several optimisation technologies will be used, depending on the complexity of the problem. This might include genetic programming as well as Machine learning techniques. The key however is to have a fast build time estimation in order to include that within the target function.

5 Part Identification

The goal of the part identification in this use case is restricted to identifying individual parts from a specific build on an AM machine. That means identifying the parts by linking the STL-files from the parts to images taken from these parts when taken from the machine.

5.1 Applicable Technology

There are currently no commercial solutions for this available on the market. There are however quite some technological approaches that could be tried here. There are two main categories of which the state-of-the-art were investigated:

- *Image processing*: The research in image processing already started in the 1960s and has provided an enormous wealth of technology to get information from (digital) images. The focus for this application is to link image data to 3D-data. Materialise has built up an extensive know-how in this area. Medical image processing, stereogrammetry, correspondence finding are all disciplines that could be used. The drawback of these methods are that they are quite computational intensive.
- *Machine Learning*: It was the goal of Materialise to use this project to investigate the applicability of machine learning techniques for this (and other image based applications). The inspiration comes from the Fashion MNIST dataset for classification which handles a related problem. Being a benchmark problem and related dataset, there is a huge amount of literature available on this subject. It still will need to be adapted to this specific problem.

There are undoubtedly other technologies which could be used in this area but these are the main ones that will be focused upon.

6 Additive Manufacturing Design Feedback

Additive manufacturing being still a newer manufacturing process, current designers need help and guidance when creating parts for this process. Whilst some parts designed originally for traditional manufacturing can in some cases be adjusted for additive manufacturing, a part designed from the get go for that process can be optimised, but only if the designer knows which features to include and which to avoid.

6.1 Currently Available Solutions

In general, Virtual Engineering (VE) denotes the concept of introducing digital models and the corresponding software tools into the product and production development process enabling collaborative and cross-discipline design and engineering processes. Thus, VE is aiming at testing new digital models early in the virtual domain against the various requirements avoiding to detect flaws later in the downstream stages when error correction becomes disproportional expensive.

Over the past 30 to 40 years, CAD tools and simulation techniques have been developed for traditional manufacturing processes and are largely used for many stages and disciplines, e.g. computer-aided manufacturing for subtractive processes, finite element analysis for structural mechanics, heat propagation, etc. and computational fluid dynamics for aerodynamics, injection moulding process, to just name a few.

Many of these tools are still used for designing shapes that are to be manufactured by additive processes. However, both in the design and in the engineering (simulation) domain, dedicated tools have been developed in recent years to address the specifics of additive manufacturing, namely the extended design space with respect to shapes that cannot be manufactured with traditional processes, the volumetric nature of AM parts and the specific simulation challenges that are induced by the AM process, e.g. heat-induced distortion of parts.

There will be an increasing demand for a software ecosystem that enables Computer Aided Technologies (CAx) to support AM processes and machines. However, to move from prototypes and demonstration 3D-models to real industrial use one needs to document and certify the quality of the outcomes of AM processes, such as product strength, surface quality, material behaviour and shape constraints.

6.2 Applicable Technology

Many research efforts have strived to develop AM ontologies by formalizing knowledge using description logic formalism to facilitate expressing domain knowledge as well as capturing information from past experiences. Using description logic on AM processes opens the possibility of representing and reasoning about AM knowledge in a structured modular hierarchy, discovering new rules with induction, and recognizing patterns with classification, e.g., what leads to “successful” versus “unsuccessful” fabrications and aid in validating hypothesized relations, as well as potentially revealing hidden ones. Hence the creation of a taxonomy, which models AM processes and materials would help solve both the issue of finding useful data and using the data to develop and improve AM processes. Creating a unified ontological framework would also reduce the fragmentation, making searching for useful data easier.

Such a framework is being adapted to manage the materials processing data provided by DARPA [31]. The taxonomy would be a solution to allow open sharing of pre-competitive data pertaining to engineering design in order to enable innovation. The taxonomy development would work on solving the issue of consistent and understandable data to both humans and computers. A taxonomy applied to engineering would represent a viable strategy for the alignment, reconciliation, and integration of diverse and disparate data. It would allow the consistent capture of knowledge pertaining to the types of entities involved; facilitation of cooperation among diverse groups of experts; effective and flexible ongoing curation and update of data; and collaborative design and knowledge reuse. Research work has been applied to the formalization of information about functionally graded materials, considering aspects of composition, application, production processes and characteristics [32]. Other research works, proposed empirically and physically based process maps that can, for example, define “safe” and “unsafe” regions for hot-working, “weldable” regions for Nickel superalloys or the transition from an equiaxed to columnar microstructure during solidification, applied to the powder bed ALM process, as alternative to costly numerical process modelling. These process maps provide a practical framework for comparing a range of ALM platforms, alloys and process parameters and provide a priori information on microstructure. They provide a reference and methodology to aid in the selection of appropriate processing parameters during the early development stages. Yicha et al. [33] developed a build orientation optimization strategy for a new FDM process, multi material deposition with continuous fibres, to improve the part quality while reducing the production time & cost. Mançanares et al. [34] developed a rationale for selecting adequate AM machinery for manufacturing a specific part, based on Analytic Hierarchy Process (AHP) that relied on a survey of AM process technologies and machines available in the market, focusing on the machines manufactured by the major players in the AM industry. Additionally, ML-based approaches were used for printability checking [35], where an estimation model was trained for printability prediction instead of using predefined rules.

7 Finding Additive Manufacturing Companies

One of the Canadian Use Case aims at producing an AM Partner search and matching tool. One solution to this problem is probably as old as time: the directory.

7.1 Currently Available Solutions

Several AM-related directories are already available. For example: 3D Printing Business Directory [36], Réseau Québec 3D [37], Canada Makes [38], Additive News [39], etc…

Similarly, there are generalist industry directories which includes AM-specialized companies. Thomasnet [40] is a good example.

Each directory solution is based on text search. There are no AM directories where the model geometry and manufacturer's experience are used as a search parameter. This speaks of the innovative aspect of our Use Case. In that respect, the closest available offering would have to be online manufacturing service providers. The likes of 3D Hubs [41], Fast Radius [42] or Xometry [43]. In those platforms, the user can upload the part he wished to create, and they will match him with one of their manufacturing partners. However, the end-user only interfaces with the platform itself, and the manufacturing partner remains hidden behind the platform. As such, we cannot consider Xometry, Fast Radius or 3D Hubs manufacturing directories, but rather manufacturing service providers.

7.2 Applicable Technology

Tools and resources to build an online directory are plentiful and well established. For example, ElasticSearch [44] and Microsoft's Azure Cognitive Search [45] can provide the foundation to powerful text-search features.

On the innovative front however, since this is a new perspective on this challenge, the applicable technology is less clearly defined. 3DSemantix' geometrical search engine [46] can definitely be leveraged, but adjustments and improvements are required to properly address this new challenge.

8 Intellectual Property Protection

Protection of the user's Intellectual Property (IP) is of utmost importance in the context on software solutions. Whilst the issue is greatly mitigated in the case of self-contained local software, this subject takes great importance in the case of an online platform.

The term *Intellectual Property* encompasses various concepts, including trade secrets, industrial designs, patents and copyrights [47]. In the context of the SAMUEL project, there is currently no need to differentiate between the types of IP.

8.1 Currently Available Solutions

IP protection online is not a subject limited to additive manufacturing, far from it. As such, best practices and guidelines have been put in place by major internet players.

The main issue is one of trust. And to prove they are trustworthy, online services rely on compliance certifications and attestation, assessed by trustworthy third-party, independent auditors.

Compliance certifications are varied, depending on the technology, services provided and regions served. Major online players usually publicly list their compliance certificates (Amazon AWS [48], Microsoft Azure [49], Google Cloud Services [50]), whilst smaller actors provide their relevant certification under request (OnShape [51]).

Relevant certifications to the SAMUEL project includes, but are not limited to:

- ISO/IEC 27000-series [52]
- AICPA SOC2 [53]
- CISPE [54]

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