Scaling Metal Additive Manufacturing from R&D to Production

by

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Abstract

Metal additive manufacturing (AM) has been successfully commercialized, yet widespread adoption has not been achieved so far. This is partly because companies struggle to operate AM factories profitably and efficiently at industrial scale.

This thesis proposes a data strategy to address this challenge and support the rapid growth and successful operation of an additive manufacturing factory – from R&D to production. The central idea is to connect relevant data to the central unit of a build. A build is proposed as one unit of manufacturing in AM. Connecting commercial data, information about geometry, processing, materials, post-processing, and testing to a build allows to gain a system-level understanding while also being able to dive into details where needed.

After implementation, the framework can be used to (i) qualify processes and certify materials, (ii) improve quoting quality and efficiency, (iii) support engineering and R&D, (iv) derive critical operations KPIs such as *revenue per build*, *builds per week*, and *days per build*, which can be used for budgeting and capacity planning as well as business control, (v) make strategic decisions on capital expenses and headcount planning, as well as (iv) ensure traceability of materials and parts. Together, these applications support decision makers as well as commercial and technical staff in their work, both strategic as well as during day-to-day operations.

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Chapter 1

Introduction

1.1 Motivation

Over 30 years after the term 3D-printing was coined at MIT [1–3], the technology has now achieved industrial commercialization and matured from prototype 'printing' to additive manufacturing (AM). Its ability to manufacture complex parts in near net-shape for high performance applications – all without the need for specialized tooling – make AM particularly interesting for the aerospace industry, but also medical products, and industrial tooling, among others [4, 5]. Additionally, using AM typically significantly reduces lead times, allows for lightweighting, and oftentimes can lead to cost advantages – critical benefits for e.g., venture-backed space companies that require speed to iterate through complex designs and achieve ambitious launch timelines. The almost unlimited freedom of design and the ability to push the boundaries in materials processing of materials such as refractory metals [6–9] provide a competitive advantage for companies that master the technology. Underscoring the significance of this emerging manufacturing technology, the US National Science and Technology Council defined AM as one of its key technology areas [10].

Inherently, AM is a digital manufacturing technology, which allows to create parts entirely based on their digital representation, without the need for specialized tooling. As such, AM is a cornerstone of what is commonly referred to as Industry 4.0 and integrates the digital world with the physical world – each process step is driven digitally and leaves a digital trace.

However, despite these manifold benefits, companies have struggled to operate AM equipment in a profitable way so far (e.g., Shapeways had a net loss of $20.2 million on a revenue of $33.2 million in FY2022 [11]) in part because doing so requires a different approach to operations than traditional manufacturing. Profitably operating AM equipment on an industrial-scale will be critical for widespread adoption of the technology, beyond niche markets.

1.2 Problem Statement

Widespread adoption of AM is subject to the commercial success of companies that are early adopters. After much research has been done by academic institutions and few large multinational companies such as Siemens and GE [12], AM service bureaus are the next wave of making AM accessible for the broad manufacturing community. These smaller companies face two challenges on the path to bringing metal AM to the mainstream of manufacturing – maturity and efficiency. On the one hand, AM has to move from individual R&D projects to actual (mass) production with parts that are used in commercial applications. Among other conditions, this requires rigorous control and qualification of material and processes. On the other hand, the scale of production has to grow from small startup-like production shops to industrial production scale with efficient operations.

This thesis outlines a data strategy and architecture that directly addresses these challenges. It supports all areas of an AM manufacturing business and allows data-driven decision making, planning, and operations control. The central element connecting different sources of data is the ‘build’, i.e., one printing process. The build allows to unite technical, commercial, and operations metrices. By means of that, an AM factory can be thought of as a conventional factory which produces ‘builds’ as its output.

The developed framework is applied within the case study of the exemplary company ‘Agouraprint’. In line with the described challenges above, the objective is to set the company up for success as it is maturing from an R&D startup into an industrial manufacturing company. At the time of this research, the AM industry is experiencing consolidation and it is critical to ensure that future operations are set up in an efficient and sustainable way. As such, this work plays an important role to support both the long-term success of AM in the aerospace industry as well as adoption in other industries.

1.3 Company Description

In this work, we will describe how the exemplary company 'Agouraprint' can use data to (i) successfully ramp up operations from a startup to industrial scale (ii) develop a digital thread centered around AM production, and (iii) convert customer R&D contracts to production orders via qualified processes and materials. Agouraprint is a research-driven engineering-technology start-up that is a leader in the area of specialty metal additive manufacturing. The company is trying to quickly scale up to satisfy high customer demand thanks to market-leading technology. Specifically, the goal is to grow the revenue more than tenfold over the next 5 years. This ambitious goal will require both (i) winning substantial customer orders in the aerospace and defense industry as well as (ii) maturing and growing operationally to be able to deliver on those orders at a significantly increased rate.

Initially founded in 2016 with a focus on materials R&D for AM, Agouraprint quickly built up a reputation of being an expert for specialty metals. By end of 2021, Agouraprint got acquired by a private equity-backed industrial company founded in 2020. With the new investment, Agouraprint got access to capital to accelerate growth of the company. Previously working out of a 4,500 sqft facility, the company recently moved into a new 40,000 sqft location outside of Los Angeles, at the beginning of this research project in May 2023. The new facility is expected to house over 15 industrial metal AM machines, metal powder handling equipment (depowdering, sieving, etc.), post-processing equipment including machining capabilities and a metallurgical laboratory, as well as other supporting equipment, inventory, and office space.

Customers of Agouraprint include companies in the commercial space as well as defense industries, among others. At the beginning of this research project, the majority of revenue stemmed from R&D-type projects focused on high-quality AM with materials that are challenging to process. The company's expertise was so advanced, that even academic institutions and national laboratories sought their help, e.g. to qualify new materials. Furthermore, many parts require significant post-processing including machining, heat treatment, and coating.

Of importance for this work, Agouraprint is a startup that had previously not put emphasis on collecting operational or technical data in a structured manner. However, customers increasingly demanded traceability and certification of material and parts. Additionally, operational data was becoming increasingly critical to control and to understand how to grow the business effectively.

1.4 Thesis Outline

Chapter 2 will provide background and an overview of the AM process with a focus on laser powder bed fusion with metal powders, describe applications of AM in the aerospace industry and the relevance of data for the digital manufacturing process. Next, Chapter 3 will lay out the central framework of this work – a data strategy. This approach will be described in detail with a focus on data sources and connection. In Chapter 4, the framework will be applied to the exemplary company Agouraprint and the different applications and use cases will be described. Additionally, light will be shed on other related considerations in scaling up an AM business. Finally, Chapter 5 will summarize the key elements and propose future research directions.

Chapter 2

Background

2.1 Additive Manufacturing / LPBF

The powder-bed AM processes for metals that are most commonly used in industrial applications are laser powder bed fusion (LPBF), electron beam melting (EBM) and binder-jetting (BJ). The three processes differ in that LPBF uses a laser and EBM uses an electron beam as a source of energy to selectively melt the cross-section of a part within a thin powder layer, whereas in BJ, the powder is initially held together by a binder that is delivered via inkjet deposition, and subsequently sintered. In order to successfully produce high-performance parts with either of the processes, detailed understanding of the underlying physics of all steps of the process is required. This includes powder deposition/spreading, the dynamics of the melt pool or binder-powder interactions, as well as heat treatments and sintering. Successful practitioners are able to control the microstructure of the final parts to tailor its mechanical properties.

In this work, we focus on LPBF as the AM process, but the proposed framework is similarly applicable to other AM technologies. In a typical LPBF machine, the feedstock powder is added to a powder reservoir (e.g., a piston-actuated reservoir, or a hopper). In the first step, a piston raises the powder reservoir platform to provide a defined volume of powder, while simultaneously, the build platform is lowered by the nominal layer thickness. Subsequently, a thin powder layer is deposited on the build platform as a spreading tool (typically a blade or roller) distributes the fresh powder

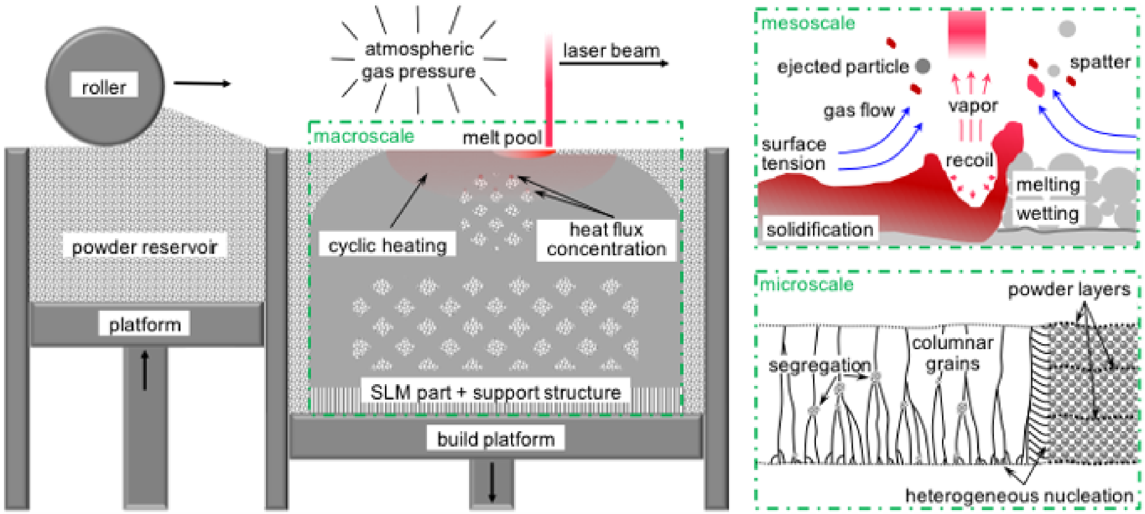

Figure 2-1: Typical configuration of LPBF process with schematic visualization of macroscale, mesoscale, and microscale mechanisms (Figure from [13])

from the reservoir onto the build platform. After the powder spreading process is finished, a laser selectively fuses particles within the powder bed, before the process chain is repeated [13, 14] (see Figure 2-1).

Operating with the optimal process parameters is challenging in LPBF and a sub-optimal parameter set can lead to defects that can cause a part to fail. Generally, the process has to be understood and controlled on the (macroscopic) part-scale (e.g., residual stresses that can warp a part), on the (mesoscopic) length scale of the melt pool (e.g., pores that can lead to cracking), and on the microscale (microstructure that determines the mechanical properties) [15, 16]. Defects can originate in every step of the process, including the powder layer prior to melting [17, 18], which is why extensive research has been conducted in this area [19–25]. While academic work laid the foundation for commercialization of the technology, the process still suffers from low build rates (i.e., <10-100 cm^3/hr per laser), which keep production costs high. Because metal AM is still a relatively new and – compared to conventional manufacturing – unproven technology, extensive manual process tuning, post-processing, and inspection are required to achieve dimensional accuracy, full density, low residual stress, and acceptable microstructure via LPBF [26–32].

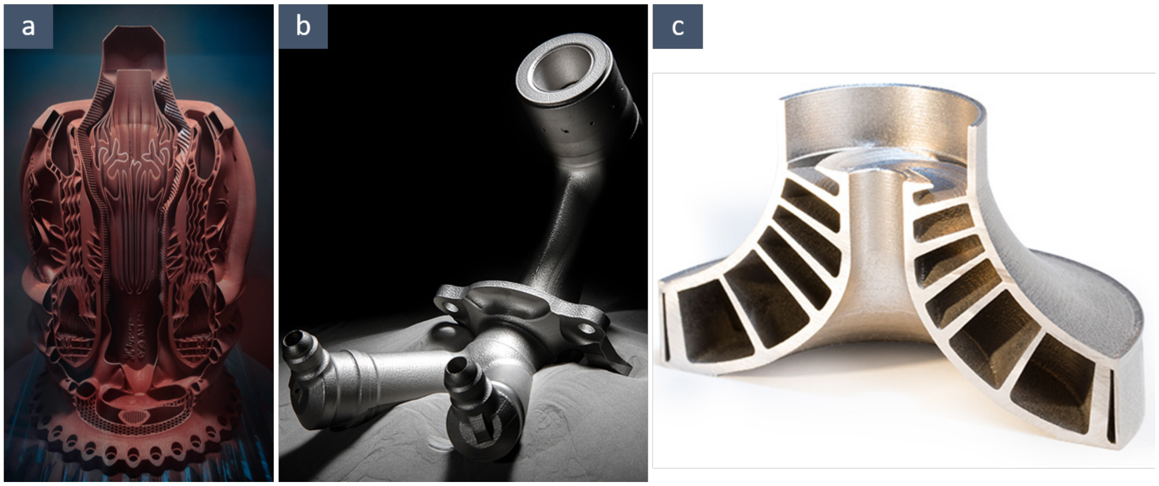

Figure 2-2: Exemplary parts produced by AM: a) aerospike rocket engine made from copper alloy CuCrZr [5]; b) mass produced and FAA-certified fuel nozzle tip [38]; c) shroud impeller [39]

2.2 AM in the Aerospace Industry

The aerospace industry is a critical part of the US economy, with a size of USD 104 billion in 2022 and a projection of USD 218 billion by 2032 [33]. The industry has both commercial as well as military applications and includes aircraft, space systems and satellites, as well as missiles [34]. Due to its nature, the industry has been at the forefront of technological innovation, mainly driven by (i) functional performance (e.g., safety-critical features), (ii) efficiency (e.g., lightweighting), (iii) cost control including lead times, (iv) sustainment and part availability (due to highly complex, low-volume components), and (v) managing complexity [35]. AM has been particularly suitable to tackle these challenges by providing advantages such as lead time reduction, cost reduction, lightweighting, consolidation of components into fewer parts, and technological improvements via novel materials [36, 37]. Exemplary parts range from aspirational prototypes such as an aerospike rocket engine printed as a single part, to mass produced parts that are certified for commercial flight, such as a fuel nozzle, as depicted in Figure 2-2.

Common materials of AM parts in the aerospace industry include aluminum alloys, titanium alloys, refractory alloys, steel alloys, and nickel-based superalloys [40]. While aluminum offers significant advantages in strength-to-weight ratio and also conventional manufacturability, which makes it a heavily used material for commercial aviation, its low melting point renders it unsuitable for high temperature applications such as propulsion systems or structural components of rockets. Titanium alloys are also commonly used in aircraft due to their high specific strength and material properties such as high temperature stability, compatibility with polymer-carbon fiber matrix composites (PMCs), no ductile to brittle transition at low temperatures, and good corrosion resistance [41]. Nickel-based superalloys have high strength and corrosion resistance, especially at elevated temperatures. Due to that, they have become the common material for propulsion system components such as gas turbine engine blades, igniters, valves, injectors, etc. [42]. Finally, for extremely high temperature applications, such as rocket or missile propulsion systems, leading edges of spacecraft or other extreme temperature applications require the use of refractory alloys such as niobium or tungsten alloys [43].

2.3 Data in AM

With the advancement of the so-called fourth industrial revolution, cyber-physical systems and the Internet of Things (IoT) are commonplace in many manufacturing facilities. As a result, product lifecycle and operations processes are increasingly organized and managed digitally. In that context, AM is naturally a key pillar of said digitally-driven production systems, as it allows to produce parts directly from a digital representation (usually a STEP file that is translated into an STL file) without specialized tooling, whereby all steps involve some kind of digital workflow.

The digital thread of a part spans all data-driven steps from design to shipping, sometimes even until end-of-life, most notably via CAx systems such as CAD, CAM, CAE, etc. [44], but also machine and enterprise resource data. Because there is a lack of a consistent framework that spans all process steps, new approaches that build on existing standards have been proposed as well, though primarily focusing on technical file format unification [45]. Promising work has also been conducted in the leverage of data for advancing AM production and processes [46]. While valuable, these proposed frameworks face practical challenges in reality, such as proprietary file formats used by machine manufacturers. The most practical approach is proposed by Mies et al. [47], with the concept of 'AM Informatics', a digital thread integrating data related to material, part geometry, AM processing, post-processing, testing as well as end-of-life – in their respective file formats. The suggested goal of AM Informatics is to (i) understand how process, material, and geometry jointly impact a part, (ii) improve the manufacturing process by increasing efficiency and reducing costs, (iii) help certify parts, and (iv) make use of the collective knowledge of distributed resources [47]. The outlined requirements of such a system are a scalable database system, flexible data schema, APIs for automated data capture, data mining capabilities, visualization capabilities, as well as appropriate security frameworks.

In order to make AM scalable in an industrial production environment – i.e., scaled operations as compared to the common small-scale R&D environments – data has to be unified across operations, engineering, materials and business functions. Since almost every step of the AM production process involves a digital representation, the execution of each step leaves a digital trace or footprint. To unify these data streams and avoid the constraints from manufacturer-specific file formats and workflows, meta-level data streams such as data from e.g., ERP (enterprise resource planning) systems can help to map different types of data in a joint schema.

While significant work has been undertaken to advance the technical efficiency and consistency of data of the digital thread and data formats [44, 45, 47], to the best knowledge of the author, no significant framework has been proposed on how to operationalize AM in an industrial business context.

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Chapter 3

Framework: AM Data Strategy

3.1 Problem Statement and Objectives

This work proposes the framework of an AM data strategy and applies it to a case study of the exemplary company 'Agouraprint'. The framework is described in this chapter. The development of the framework is motivated by the situation of the company 'Agouraprint'. Agouraprint is trying to significantly grow their revenue by more than an order of magnitude over 5 years, maturing from an R&D startup into an industrial production company. This will require both (i) winning substantial customer orders in the aerospace and defense industry as well as (ii) maturing and growing operationally to be able to deliver on those orders. Agouraprint is a startup that had previously not put emphasis on collecting data, but rather worked in a job shop-like environment. As the company was growing rapidly, capacity and resource planning as well as business control on a per-order basis were required.

3.2 Broad Approach

The proposed approach builds on the idea of leveraging data to make informed, data-driven decisions in all areas of the business. The company was in the rare situation of essentially starting greenfield from a digital perspective, without any legacy systems or data infrastructure. This can be both a catalyst for fast change as well as a challenge due to a required evolution in culture and mindset. In that environment, data from different sources was generally not collected and if it was collected, it was not connected. To tackle that challenge, an ERP system was implemented, a data warehouse was established, and data from different sources were connected via these two systems. The detailed framework that is described below extends on some of the ideas of AM Informatics [47] by moving beyond technical data and including operational and commercial data as well. A new data schema that is targeted at operationalizing AM is introduced in the below. By combining technical, operational, and commercial data, the power of the framework increases tremendously and allows to make business decisions on a system level as well as on a per-part level. Ultimately, this will allow to both (i) win substantial customer orders as well as (ii) mature and grow operationally. First, winning customer orders requires qualified processes and materials, traceability of parts and materials, industry standard certifications, cutting edge R&D, as well as a high quality quoting process. Furthermore, manufacturing on an industrial scale requires effective planning and business control, both on a system level as well as on the detailed level of single parts. All of these elements are enabled by the presented framework and are elaborated on in Chapter 4.

3.3 Description of Approach

3.3.1 AM Factory Process Flow

Before diving into the structure of the data strategy, it is important to first understand the intended process flow of an AM factory.

Figure 3-1 outlines the general factory process from initial customer request to shipping. In what is denoted as 'pre-manufacturing', the commercial and technical details of an order are defined between supplier and customer, before an order moves to manufacturing. Here, data is generally generated and handled on a 'per order' basis. First, the customer creates a request for quote (RFQ), the initial order description that triggers the supplier to start acting. The supplier then estimates both lead time as well

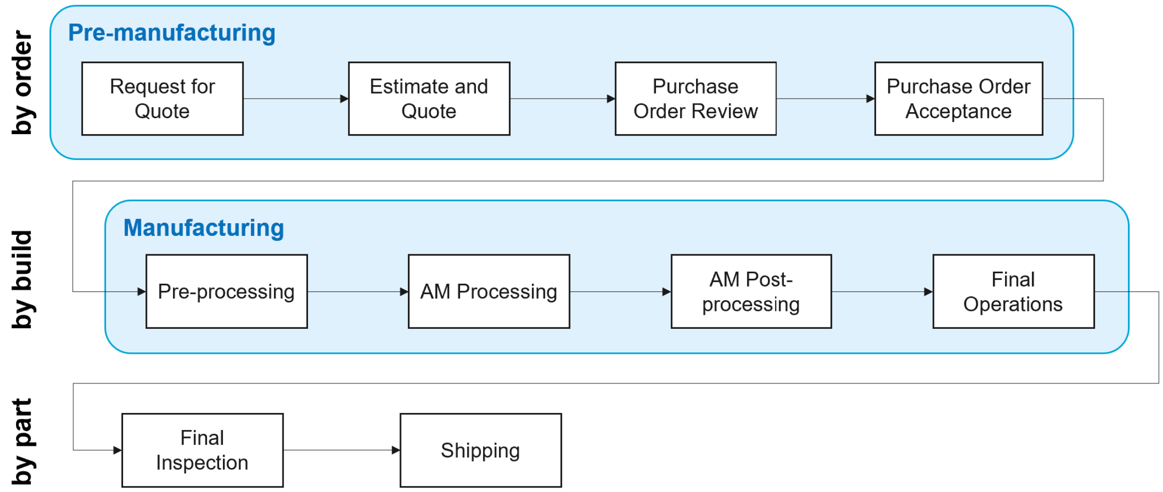


Figure 3-1: AM Factory process flow, with indication of the level of joint operations – by order, by build, or by individual part

as price and other technical or contractual requirements and generates a quote. When the customer agrees with the quote, a purchase order is generated and sent to the supplier. The supplier has to review the purchase order from several perspectives, such as commercial, manufacturing, and quality. Finally, when all involved stakeholders approve the details outlined in the purchase order, the order is accepted and gets routed to the actual manufacturing part of the factory.

From a manufacturing operations perspective, machines are operated by build (instead of per order). A build is defined as one unit of manufacturing that physically is represented by one build platform with the respective parts that are printed on it. That means, that as soon as the order is accepted and moves to the manufacturing step, data will be generated on a 'per build' basis as the build is moves through the factory, relatively independent from the order. Here, the order-to-build mapping can be a one-to-one, one-to-many, many-to-one, or even many-to-many. Usually, a company would start out with one-to-one, or one-to-many, meaning that one order is filling one or multiple build plates, but orders are not combined on build plates. However, in order to improve efficiency, nesting is a critical step to ensure that the available build volume is used optimally. This can lead to a many-to-one or even many-to-many mapping. A many-to-many mapping is a situation, where one order has parts distributed on multiple builds, but the respective builds also include parts from other orders. For example, if one order contains multiple larger parts that use 60% of the build volume, the remaining space can be used by parts from other orders. This in turn creates complex data relationships, for example when analyzing the profitability of an order as well as of an individual build.

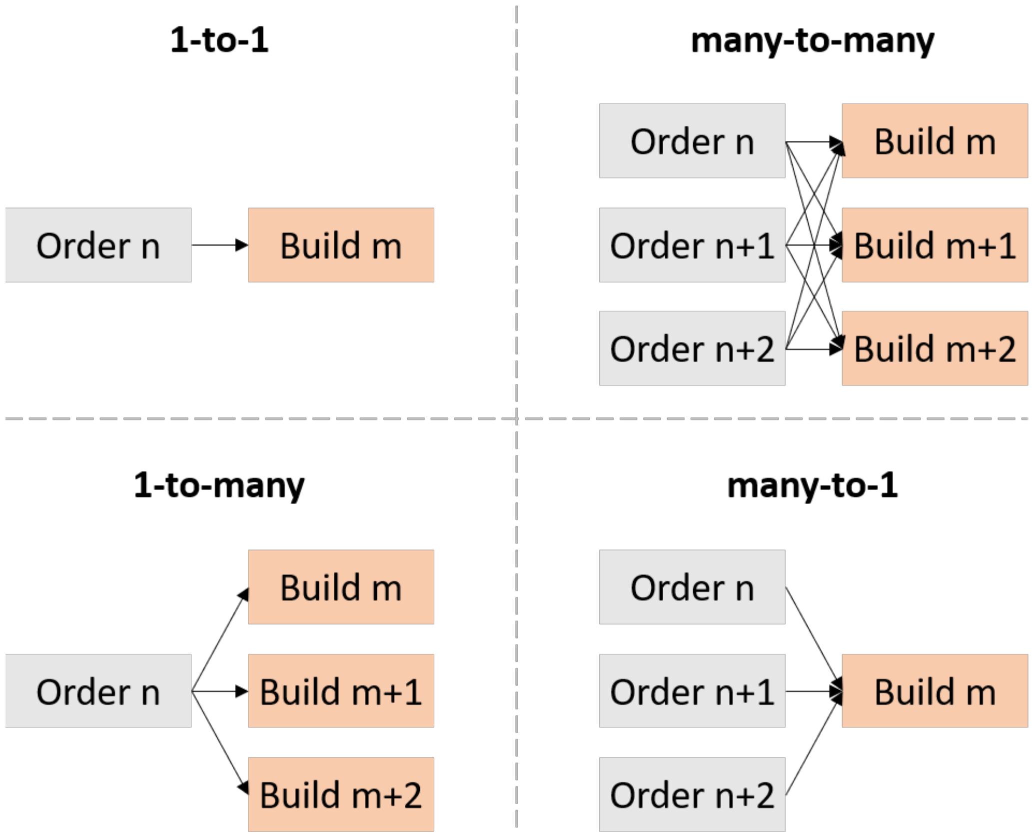


Figure 3-2: Schematic of potential order-to-build mappings in an AM factory

The first step in manufacturing is the AM pre-processing. Here, AM engineers review the technical requirements of the order (drawings, material, etc.) and create critical documents such as an operations traveler, a quality plan, and a post-processing plan. If required, CAD modifications are implemented, for example extra adding stock to the as-printed part if subsequent machining operations are required (e.g., for holding the part). Finally, the build file is created and reviewed before it gets transferred to the printer. Next, in the AM processing step, an AM technician sets up the machine and documents relevant technical data such as the weight of the build plate, the material lot number or the weight of the added powder. The machine gets loaded with the build plate and powder and the print is started. Oftentimes, prints in large commercial machines can take multiple days or, in some cases, even up to two weeks to process. Throughout this printing process, technicians and engineers regularly check the printing progress at critical check points, for example when a significant change in the part cross-section is occurring. After the print is finished, the machine and part have to cool down before the AM post-processing can begin. In parallel to the print, technicians also execute powder handling operations, such as sieving or mixing of powder, that has to be documented for traceability reasons. After the build has cooled, a technician removes excess powder from the build plate in the machine, removes the plate and records data such as the weight. The build usually has to be depowdered in a dedicated machine or cabinet because powder can get entrapped in internal channels or in the print support structures. After a first visual inspection and additional documentation, print artifacts such as witness coupons are obtained as well. After the build is finished with the AM operations, the final operations begin. Many builds first get sent to a stress relief heat treatment, before the parts get cut off the build plate, usually with a wire electrical discharge machine (EDM). Now, parts can be cleaned, deburred, and support structures are removed. Usually, a dimensional inspection is conducted as well, before additional post-processing steps are initiated. With individual parts at hand, additional heat treatment steps can be done, such as hot isostatic pressing (HIP). Other steps include machining of critical surfaces, applying coatings, destructive material testing with witness coupons as well as non-destructive testing via X-ray or computed tomography (CT). Finally, individual parts go through final inspection and documentation before they get shipped to the customer.

As described above, a significant amount of data is generated both manually (e.g., documentation) as well as automatically (by machines or systems) across all process steps. Capturing that data in a structured way and leveraging it best is the goal of the proposed strategy.

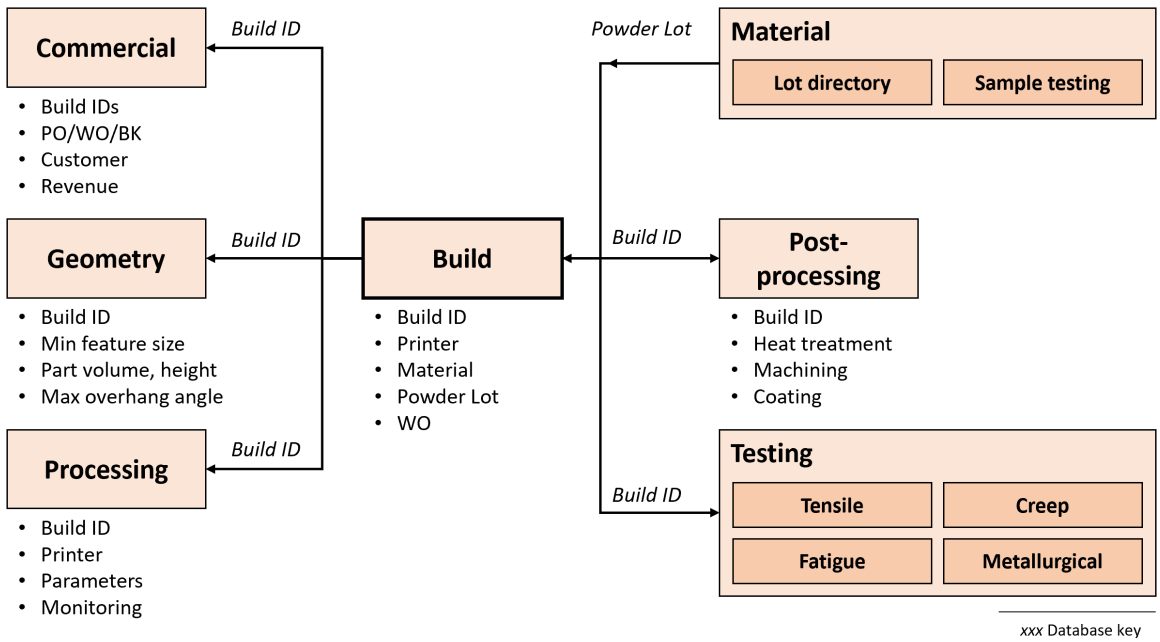


Figure 3-3: Overview of data strategy schema

3.3.2 Structure of the AM Data Strategy

The fundamental idea of the proposed data strategy is that everything in an AM facility centers around builds. As described earlier, a build is defined as one unit of manufacturing that physically is represented by one build platform with the respective parts that are printed on it. A build has many other properties, such as the time when it got started, the time it took to complete, the material that was used, etc. In order to manage an AM factory, the build can be used as the central unit of manufacturing, that represents the product of the factory. In analogy to e.g., an automotive factory, one build in an AM factory would be equal to one car in an automotive factory (Note: in this example, the previously mentioned mapping of order-to-build would only include one-to-one and one-to-many since one car cannot be part of multiple orders). As such, critical key performance indicators (KPIs) such as production output or defect rate can be easily calculated and understood.

Figure 3-3 outlines the structure of the proposed AM data strategy, in the form of a data schema. Each box represents a database/table or repository of data, and all of these databases are linked to each other via a database key, indicated in italicized letters on the arrows. At the center of the data schema is the build – or in this case a table of builds. This table, the 'build log', contains basic information of a build, such as the build ID, the printer it is being processed on, the material, the powder lot, and the work order (WO) it belongs to, which allows to quickly understand the basic information. Most of this information is redundant and pulled from other databases. In addition to the database key, usually the build ID, the following will briefly describe the content of each linked data repository.

Commercial: To leverage the data for operations and management decisions, commercial data has to be linked to each build. That includes information, such as to which purchase order (PO), work order (WO), or booking number (BK) the build ID belongs. These numbers are typically generated in commercial systems such as a customer relationship management tool (CRM). Oftentimes, the purchase order coming from the customer has a unique identifier, but can then be broken down further. For example, a purchase order could be a frame contract that contains multiple bookings, which in return could be covering content that requires multiple work orders to fulfil. Possible many-to-many mappings can be created in these situations, as described above. Additionally, the commercial information includes the customer and usually a customer ID in the system, as well as the associated revenue to each build. The revenue is critical and can usually be derived from the purchase order by allocating the respective revenue associated with all parts on a build. Additionally, cost information is linked to the build as well, as will be described later.

Geometry: Besides the actual part files, this repository contains critical information such as the part volume (e.g., to calculate material consumption), as well as the height of the build, which is a key factor determining build time. Furthermore, critical component information such as minimum feature size as well as maximum overhang angle can be reported.

Processing: From a processing perspective, the machine that is used to manufacture the build is recorded, as well as the print parameters used for the print. If the data is collected, monitoring data is stored in this category as well, e.g., data about temperature, oxygen content, images from the build, etc.

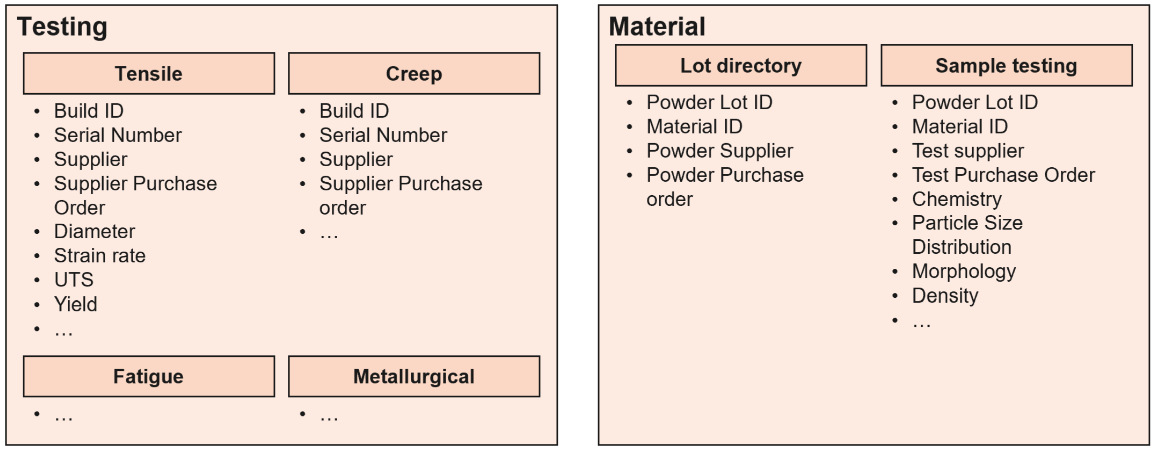


Figure 3-4: Detailed outline of the material as well as testing data repositories

Post-processing: As described earlier, almost all builds will require some kind of post-processing. For each of the steps, critical information has to be recorded. For internal processes, that includes the machine used, as well as the process parameters, incl. processing times; for external processes, that includes vendor, cost and process information, including e.g., heat treatment recipes or coating procedures.

Testing: Mechanical and material testing data is critical for part qualification and process control in manufacturing. Especially when R&D projects push the boundaries of the state-of-the-art, it is of utmost importance to have rigorous testing procedures and documentation. For that reason, the testing data repository is described in more detail in Figure 3-4. Key test data includes data regarding mechanical properties such as tensile, creep, and fatigue behavior. Because these data points are on a part level, and not on a build level, in addition to the build ID, also the part serial number has to be recorded. That serial number links the test specimen, e.g., a tensile bar, to the location on the build platform as well as the build orientation, which is information that is recorded as part of the build layout/geometry. If suppliers are used, the relevant information includes the supplier, the PO, the tensile bar diameter, recorded strain rate, UTS, yield strength, etc. Similar data is required for other types of testing, including metallurgical testing, which might include information about the microstructure, such as grain size, or the chemical composition.

Material: As described in Figure 3-4, the material information corresponds to the raw material used. Since one powder lot will likely be used for several builds, this is the only repository/table, that uses the powder lot as database key. For traceability of material it is critical to record the powder lot for each build, including key information such as the supplier as well as powder sample testing data such as the particle size distribution (PSD), analysis of the chemistry, particle morphology, etc. For accounting purposes, cost information is also recorded here.

3.3.3 Data Sources and Collection

The outlined data schema draws on a variety of data sources from all across an organization, which ideally get fed automatically into a data warehouse. One central tool is the enterprise resource planning (ERP) system, often in combination with a material requirements planning (MRP) system. These systems generate, and allow to access, central elements of the data schema, such as a build ID, and operations data such as timestamps, duration of processes, operators, materials (incl. IDs), etc. Together, they cover most elements from the sections 'Build', 'Commercial' (in combination with the customer relationship management system), 'Processing', 'Material', 'Post-processing', and some elements of 'Testing'. More technical elements from 'Geometry' as well as 'Testing' (e.g., test data), are generally stored in separate databases, which can be automatically linked in the data warehouse.

3.4 Limitations and Challenges

While the outlined data strategy is very comprehensive and covers a wide array of elements from a manufacturing business, it relies on high quality data inputs, ideally from the sources described above. The quality of decisions based on the data is only as good as the quality of the data inputs. However, in reality this highly depends on the infrastructure, maturity, as well as the culture of a manufacturing business. In very young companies such as startups, as well as companies that do not focus on quality of data, the data input can be challenging. If a company does not yet have e.g., an ERP system, many of the above mentioned data points can be arduous to collect. It might require manual documentation of e.g., a build log, analysis of individual printer data, digitization of paper-sources such as material test reports, etc. The manual creation of a build log for example spans across multiple disciplines and requires to understand which build is started when and on which machine, which parts from which customer are placed on a given build, and how much revenue from a PO is associated with these parts. It might require reading POs and searching for the relevant information, and then tracing this information to a build. On the other side, it requires manually understanding which powder lot is loaded to each printer, and the cost associated with said powder lot. Having a well maintained digital system that keeps track of all of these elements thus is critical for the success of implementing such a data-based strategy. On the other hand, the company culture is also a critical element for the success of such an initiative [48]. The culture often dictates the quality of recorded data. If the culture emphasizes high quality data, and a high standard of documentation, it allows for significantly more insightful analysis later on, compared to e.g., a culture where documentation is pushed off to the last day of a reporting period and then completed to the absolute minimum. The effects of this ultimately impact the operations of a company, with a stronger focus on a data-driven culture significantly improving operational performance [48]. Furthermore, a data-driven culture has been shown to promote a higher level of innovation in organizations, as firms that focus on data are able to introduce new products and optimize organizational processes more effectively [49]. A cultural journey of a company can start with just creating awareness for the importance of high quality data and establishing best practices, as simple as how to best save and catalogue information. As a next step, creating a higher level of data literacy involves also focusing on data security, since data is becoming more of a central asset of a company [50]. In a final step, a company should become a data-driven company, where decisions are informed by the analysis of high-quality data and people put trust and pride in the data of their company. Unsurprisingly, leadership support is critical for the successful cultural transformation [49, 51, 52].

Chapter 4

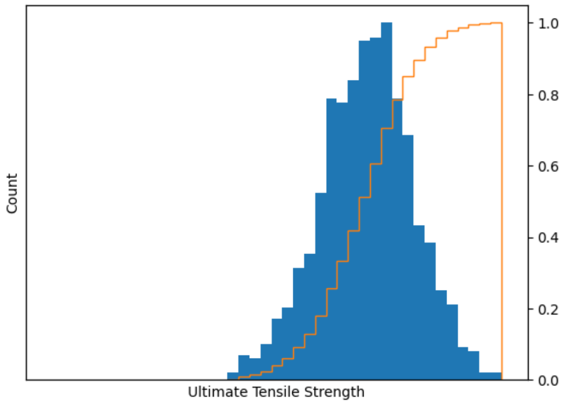
Applications and Results

The framework described in Chapter 3 can be used for a variety of purposes in a company. This chapter applies the framework to the exemplary company Agouraprint and describes use cases that are relevant for an industrial company that is scaling up operations. Specifically, the goal is to both support technical processes as well as strategic business decisions [51].

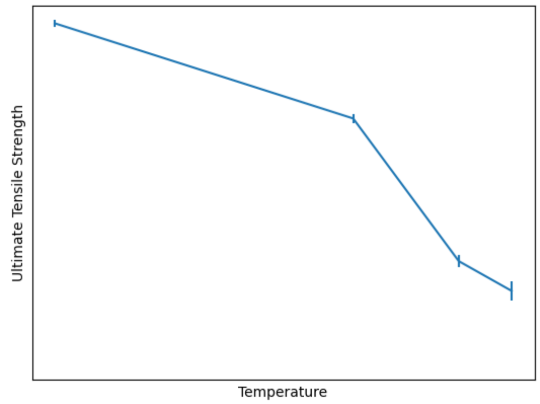
4.1 Process and Material Certification

Agouraprint is a young company that differentiates itself through technical expertise in materials and manufacturing processes – specifically the metal AM of specialty metals. Because of its understanding of the process and materials, customers often ask Agouraprint engineers to support the R&D process of new components or materials. While this work allows to tap into a market niche that few companies occupy, it also comes with challenges. In order to move from the initial R&D projects to production orders, customers might require proof of process control leading to consistent material properties in final parts. Production orders are usually more financially attractive than R&D orders because the same parts can be produced multiple times. This allows to amortize non-recurring engineering expenses over more parts and also frees up valuable engineering capacity.

With the data schema, material test data such as tensile tests are linked to their



(a)



(b)

Figure 4-1: Exemplary analyses of material testing data (artificial data generated for visualization purposes), depicted for ultimate tensile strength (UTS): (a) UTS testing results performed at one temperature grouped into bins (blue bars) and translated into a cumulative density function (orange line); (b) Mean UTS for tensile tests performed at various testing temperatures, standard deviation depicted as errorbars

respective builds and can be easily accessed in a structured manner. This allows to create process control charts (also known as Shewhart charts) based on test coupon data, but also to analyze material data in a statistical manner. For qualifying e.g., ultimate tensile strength (UTS) of a given material, all test results can be aggregated to a probability density function as well as a cumulative density function, as shown exemplary in Figure 4-1a. This allows to provide a level of confidence to the customer about the achievable material properties. Based on these material properties, customers then can confidently design parts.

Additionally, the analysis of material properties across a range of (elevated) temperatures is relevant for applications that require specialty metals. Agouraprint can use a helpful representation by plotting the mean of a given property against the testing temperatures, and adding errorbars representing the standard deviation of the distribution (see Figure 4-1b. Customers can easily understand how the strength changes as the part is exposed to elevated temperatures.

Agouraprint used these analyses to create a material data sheet for 'standard' materials, which is valuable for sales activities and critical for capturing contracts in the aerospace and defense industries.

4.2 Quoting

As a rapidly growing company that provides engineering services and manufactures highly engineered parts, quoting became a significant challenge and time commitment for the Agouraprint team. Quoting is a challenging task because the supplier has to provide a price and lead time estimate, usually with incomplete information. If a project is misquoted, it might lead to either not winning a contract or winning a contract at a low (or negative) margin. However, one has to be efficient during quoting because it is unpaid and simply lost time if a quote is not successful. Depending on the win-rate of a company, the number of quotes that have to be created can be significantly higher than the number of customer projects that are ultimately executed. Thus, generating profitable quotes that win customer orders are a critical step to setting a business up for success.

There are generally two approaches to quoting – the cost-plus approach and the customer-value approach. For the cost-plus approach, the quoting team assesses the expected costs of executing a project and then adds a profit margin on top. This is common in a competitive market where the products or services are comparable. The customer-value approach differs in that it shifts the perspective from the supplier's cost structure to the customer. The price is essentially set to be the willingness-to-pay of the customer. This is often difficult because it requires knowledge about the willingness-to-pay as well as the absence of competitors that might compete on price. With its often unique value proposition, AM is an example of where value-based pricing can succeed because it can produce parts that cannot be manufactured by other processes. Some examples include e.g. healthcare/medical device products [53]. Frequently, AM wins projects based on the unique value proposition instead of a competitive price. However, even when quoting for value, understanding the cost structure is important because the own cost structure sets the floor price to avoid projects with a low/negative margin.

Quoting the highly individual or specialized projects that Agouraprint executes is challenging because of the lack of a benchmark (e.g., past experience). For a company that does mass production, creating a quote is simpler – most costs are established and the process of making the product is proven. For Agouraprint, projects often start with customers trying to solve a problem that has not yet been solved. Specifically, this might involve novel materials or parts that have overhang angles that are challenging or geometric features that are difficult to manufacture. Having a documented history that connects critical information about the parts, the quoted price, as well as the actual incurred costs for projects allows to build up a benchmark and learn about the accuracy of previous quotes. This in turn allows to improve quoting quality (more accurate quotes) and efficiency (faster quoting) over time, which can have a significant financial impact.

In addition to the raw numbers, the context of a project also has to be considered when analyzing the data. For example, a complex R&D project might be quoted and executed without profit, if it promises significant follow-on production orders that offer a high margin. In that case, executing the project might be considered the cost of business development for winning that larger follow-on order, or potentially even a new customer.

4.3 Engineering and R&D

As mentioned, Agouraprint does a significant amount of R&D work on challenging geometries, novel materials, or trying to enhance properties of existing materials. The data schema allows to analyze part performance for different print parameters or material compositions, supporting the research process. When customers ask for challenging geometries or features, the repository allows to search for these part features in the history and to quickly understand if and how said features were possible to successfully manufacture in the past.

Another challenge engineering faces is transferring production parameters between machines. The machine park of Agouraprint includes a variety of machines from different OEMs that differ in specifications such as build volume, number of lasers, laser power, and laser spot size. Manufacturing of novel materials is usually investigated on smaller machines because research powder feed stock is expensive, machine change-over is quicker with smaller machines, and the cost of running a smaller machine is lower (both actual cost as well as opportunity cost). However, once a novel material is qualified and can be moved to production, the print parameters generally have to be transferred to a different machine. This can be challenging and in the worst case involves going through multiple iterations of process qualification which is costly and takes time. Being able to transfer parameters effectively and qualify a certain material on a new machine on the first iteration thus is critical. Having a history and clear understanding of the process first principles allows to significantly accelerate this process.

4.4 Budget and Capacity Planning

4.4.1 Revenue per Build

When running AM machines in an industrial setting, the goal is generally to maximize profitability and/or business growth. One central objective achieved with the data strategy is the combination of commercial data with technical and operations data. This allows to understand the revenue and associated costs of each individual build that is processed in a facility. Remembering the analogy to automotive products given in Chapter 3.3.2, each build is like one unit of manufacturing of an AM factory. Understanding the profitability of each unit is thus of utmost importance for running a factory.

The profitability of a build is a result of the revenue that is made with each print negative the costs that are associated with the build. While a detailed cost accounting of all relevant costs is essential, for the purpose of clarity in this work we will make the simplifying assumption of not considering the cost side for now. While this is a strong simplification, the different cost components can be analyzed via the described data as well in order to get to an actual profitability value. Some of the most important cost drivers are material costs (calculated via part volume and raw material cost), labor

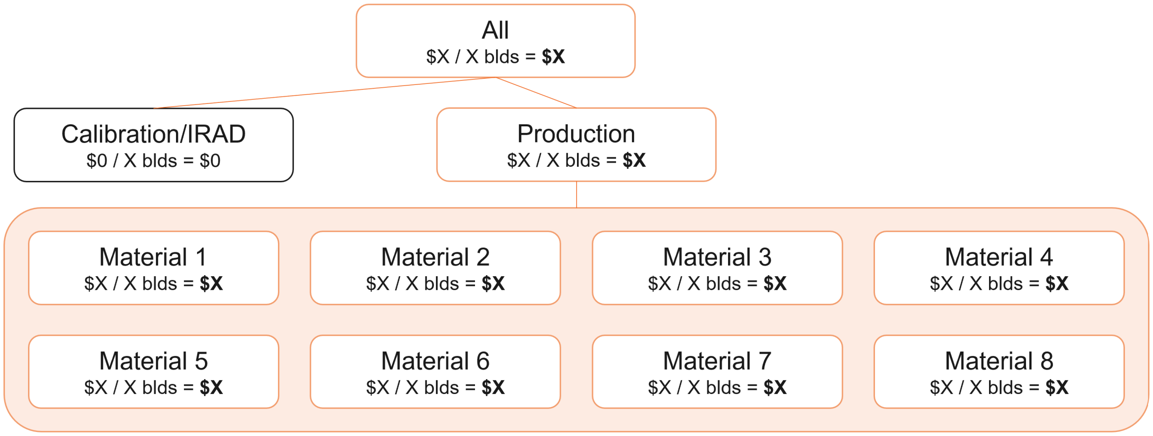


Figure 4-2: Exemplary visualization of revenue analysis by materials

(e.g., engineering and technician time), machine depreciation, utilities (e.g., electricity, argon), and third party costs from outsourced process steps. Because of the relatively standard nature of the labor steps, time-driven activity-based costing [54, 55] is a suitable approach for profitability analysis of builds.

The revenue of a build is primarily driven by the occupied (solidified) volume of the build, which also drives build time and material consumption, as well as the material. In order to maximize build volume utilization, the available build volumes on each machine are usually filled as much as possible. Distinguishing machines by build volume allows to focus on material as the critical factor for print revenue. The range here can be significant, ranging from almost commoditized materials such as steel alloys on the low end to refractory metal alloys on the high end. The associated revenue for a comparable geometry can differ by more than an order of magnitude depending on the material, making the understanding of materials a central business element. Figure 4-3 shows an exemplary visualization of how the revenue of prints can be broken down first by revenue-generating vs. non-revenue-generating (i.e., machine calibration and internal R&D or IRAD), and then further by materials. For Agouraprint, this analysis allowed to quickly understand the relevance of certain materials as central business drivers.

4.4.2 Builds per Week

Understanding the revenue of each build allows to understand revenue drivers and what drives the business, but it is also critical for capacity planning. As common for companies with a business plan, Agouraprint has a certain revenue goal for each reporting period. The average revenue-per-print allows to quickly translate this commercial number into an operations number. For example if the goal is to make $100 revenue per month and each build on average generates $10 revenue, this translates to roughly 2.5 builds per week (assuming approximately 4 weeks per month). Knowing this number, Agouraprint's manager can determine the required staffing levels. For AM machines, labor primarily scales with the number of prints (as compared to the length of prints), so over a certain time period (e.g., a week) the KPI of *builds per week* is critical to monitor. To run one build per week, Agouraprint needs to have the engineering capacity to set up the build, the technician capacity to prepare the machine and post-process the parts, etc. For that purpose, Agouraprint ran detailed analyses of the labor capacity needed to complete each step in processing a build. For example if one engineer can process one build per week, Agouraprint would need at least 2.5 engineers for that production rate.

On a higher level, builds per week is the factory throughput of an AM facility. Because print times are often on the time scale of around one week, this time period makes intuitively more sense than what is often used in other manufacturing processes (e.g., per day or per hour). Monitoring the throughput and operations capacity in parallel to the financial performance allows to disentangle operating performance from other factors such as pricing or sales mix. Because Agouraprint was on a steep growth path and most prints took a similar amount to run, operational excellence and ramp-up planning was done using prints per week as a KPI. For example, during the time of this research work, processes were optimized to increase builds per week, which resulted in an increase of the throughput by a factor of 2-3. While the labor content scales with that increase in throughput, dedicated process improvements (e.g., Kaizen workshops) are required to improve the labor efficiency so that prints per week can increase faster than labor. Agouraprint was able to scale throughput significantly faster than headcount thanks to an adjusted team structure and process flow.

4.4.3 Days per Build

Taking the inverse of the builds per week KPI, Agouraprint was also able to analyze the *days per build*. In contrast to labor, which scales primarily with the number of builds, required machine capacity scales with the number of available days per build and the actual time it takes to run a print. Remember the $100 revenue per month example from above, where one build generates $10. In addition to knowing that it takes approximately 2.5 build per week of throughput, one can also conclude that the time for the builds is approximately 3 days per build (assuming approximately 30 days per month). Assuming that an average build runs for 5 days, Agouraprint needs at least two machines to process at this production rate. At Agouraprint, this analysis is more complex because the company processes a variety of materials that oftentimes are tied to certain machines, and has machines with a wide range of build volumes and processing speeds. For example, changing materials might not be desirable due to the risk of material contamination. In addition, Agouraprint serves a variety of customers in various stages of the product development cycle. Understanding the sales mix (by material and length of builds) was critical in that case to manage potential machine bottlenecks. Due to these reasons, for Agouraprint, the *days per build* are analyzed per machine to ensure capacity constraints are not reached.

4.4.4 Budgeting

With the three KPIs *revenue per build*, *builds per week*, and *days per build*, Agouraprint was able to plan capacity and create a budget for the following reporting period. The team analyzed each project in the sales pipeline by probability of success, material, and where possible even the expected machine that a potential project might run on. This allowed Agouraprint to break down the expected revenue for the next year, and what that revenue figure meant operationally in the factory. With historical value per print

			Base – Budget		Max capacity	
Printer	**Material**	**Value / Print**	**Prints / Year**	**Revenue / Year**	**Prints / Year**	**Revenue / Year**
AM machine 1	Material 1	$\$X_1$	Y_1	$\$X_1 * Y_1$	Z_1	$\$X_1 * Z_1$
AM machine 2	Material 1	$\$X_2$	Y_2	$\$X_2 * Y_2$	Z_2	$\$X_2 * Z_2$
AM machine 3	Material 2 & 3	$\$X_3$	Y_3	$\$X_3 * Y_3$	Z_3	$\$X_3 * Z_3$
...	...	...	...	...	...	...
AM machine j	Material n	$\$X_n$	Y_n	$\$X_n * Y_n$	Z_n	$\$X_n * Z_n$
Total			**SUM(Y)**	**SUM(X * Y)**	**SUM(Z)**	**SUM(X * Z)**
		Prints/week:	*SUM(Y)/52*		*SUM(Z)/52*	
		Days/print /machine:	*365/MEAN(Y)*		*365/MEAN(Z)*	

Figure 4-3: Exemplary breakdown of an annual revenue budget by machine with key KPIs

figures, the team was able to determine what the approximate factory throughput (by machine) would have to be to achieve the budgeted revenue. Subsequently, that factory throughput informed headcount planning as well as capital expenditure planning both for AM equipment as well as post-processing equipment. An exemplary, simplified view of a breakdown of an annual (revenue) budget by machine, that can be used to understand capacity limits and headcount planning.

4.5 Business Control

4.5.1 Monitoring Operations KPIs

In addition to the planning process described above, the defined KPIs are also critical for business control. The factory manager needs to be able to review these figures in a dashboard on a continuous basis to ensure business success. The dissection of the different KPIs allows to quickly tell why performance is changing. For example, if revenue is above target, this might be due to pricing (represented in revenue per build), material mix (represented in revenue per build broken down by materials), increased throughput (represented in builds per week), mix of the type of projects (represented in days per build), etc. Because the underlying data is connected to technical data, the manager is able to dive deeper into the data, for example by getting a breakdown of the KPIs by machine or by material.

4.5.2 ROI of Printer

Agouraprint was growing its metal AM printer fleet significantly to support increasing demand for products and services. When deciding on a new significant capital investment into an asset such as an AM machine, many factors are taken into consideration. One central decision factor is the financial impact of making the investment – commonly calculated via the return on investment (ROI). There are multiple ways to think about it (e.g., discounted cashflow analysis, payback time, etc.), but it always comes down to comparing the cost of the asset to the expected return of having/using the asset. For Agouraprint, this meant thinking about the expected operating gross profit a printer could achieve over its lifetime. Because this analysis looks into the uncertain future of a fast-paced company in an industry that is still in its infancy, reliable data is challenging to attain. In order to calculate an ROI, one needs to understand the expected revenue and costs per year and the number of years of lifetime of the equipment. The revenue per print metric in combination with an expected utilization (prints per year) allowed Agouraprint to quickly understand the revenue potential of a new machine. Time-driven activity-based costing for all labor elements as well as expected material costs and historical values for other order related expenses (e.g., post-processing) allowed to estimate the cost side which in turn yields a profitability (gross operating profit per year). These metrics made it possible to quickly assess the viability of new investments. For Agouraprint, one conclusion from the analysis was to pursue larger machines as well as to focus machines on materials that are high value and have a relatively substantiated sales pipeline (i.e., lower level of uncertainty).

4.5.3 Ratio of Labor to Asset Costs

From a management perspective the two metrics builds per week and days per build bring an interesting fact to light. Assuming an identical utilization of an AM machine in terms of print hours per year, there are two ways to run the machine. The first option is to run long prints, which result in low builds per week and high days per build. The second option is the reverse, with short prints resulting in a high number of builds per week and a low number of days per print. A business with many short prints will likely have higher labor costs than a business with fewer long prints, because the labor content scales with the amount of builds (setting up the build, turning over the machine, etc.). It also allows to offer shorter lead times because parts will be out of a machine in a higher frequency. Running an AM machine is essentially like running a train. Every time the machine starts, it's like closing the door on a train – if a part is not loaded onto the build, it will have to wait days for the next print to start and there is no flexibility or possibility to change the production order without losing all progress made on the started build. However, running longer prints likely requires machines with a larger build volume which are generally more expensive. Thus in this case, the asset costs or capital expenditures will be higher, in return for relatively lower labor costs. This means that parts can be produced in lower frequency, but at a higher labor efficiency.

Of course, there are also other considerations that have to be taken into account, such as the required size of parts, portfolio of different materials that might require different machines to avoid material changeover, etc. In reality, Agouraprint needed to carefully weigh these different factors in order to determine the optimal mix of large (i.e., long builds) and small (i.e., short builds) machines.

4.6 Traceability

Since Agouraprint primarily operates in the highly regulated aerospace industry, traceability of material and parts, as well as documentation of the manufacturing process is critical. For example, this is an important step in order to qualify and certify AM parts "for NASA spacecraft systems, including, but not limited to, crewed, non-crewed, robotic, launch vehicle, lander, and spacecraft program/project hardware elements" according to NASA standard 6033 [56].

The data warehouse which stores all data as described, is a critical tool to achieve this requirement. If Agouraprint for example would detect quality issues with a certain raw material powder lot, it could quickly determine which previous parts were produced using the same powder lot. The same holds true for process parameters, post-processing routines, etc.

4.7 Discussion and Organizational Considerations

The presented data strategy is relatively comprehensive but is only one element of the effort needed to scale up an AM business from an R&D work to industrial-scale production. This section describes some of the considerations from implementing such an endeavor as well as other challenges and organizational topics from scaling up an industrial business.

Agouraprint came from a position of being engineering-driven and very lean – a startup. This meant that few people were doing many tasks at the same time and documentation was not necessarily required to the same extent as customers would expect it from an established, mature company that produces parts for serial production end-uses. To improve on this fact, Agouraprint decided to implement a CRM system as well as an ERP system. This also came with a change in culture and required changes in processes. Documentation became a central element of daily work which initially can cause frustration because it can slow down processes. A cultural change was needed that focused on high quality data capturing because a data strategy is only as good as the data entered into the systems. This included creating awareness through training and educating, teaching best practices, as well as setting up the infrastructure and processes to make documentation easy, for example through tablets with custom interfaces for shop floor technicians. Implementing a sophisticated system such as an ERP that spans the entire company, takes a significant amount of resources – both time and money (e.g., implementation times of over one year are not uncommon for medium sized companies [57]). In parallel to implementing company-wide systems, other parts of the data strategy, such as the materials data base could be implemented separately and only get merged later on in a data warehouse. Because for example a material scientist is often not naturally a data scientist, an internal change agent or outside help that can accelerate these projects is critical.

This also presented an opportunity to challenge existing processes and responsibilities, which was required as part of the broader scale-up of the company. At the same time as new systems were being implemented, the company moved facilities to increase footprint tenfold, acquired, installed, and qualified machines that increased production capacity by a factor of 2-3, and increased headcount to support the growth. With so much growth and maturing happening on all parts of the business, a central challenge is keeping daily operations as stable as possible, while employees have to be trained and onboarded or are supporting the growth initiatives. A very effective approach to make this happen at the same time was to simplify to the most fundamental level and then accelerate from that position of stability. On an organizational level, this meant breaking out new roles that would reduce the amount of different tasks per role. For example, all AM engineers used to work on both quoting as well as build file preparation/customer consultation. A new role was introduced where one of the AM engineers specifically only worked on quoting full-time whereas the others would focus on handling ongoing projects. Operationally, visual management was used extensively to focus on the most important things. For the shopfloor technicians, the critical reference time frame is one day. To focus the team on 'winning the day', an operations board was established where daily standup meetings were held to discuss priorities and work plans (i.e., who is doing what until when). As a second level, the operations leader and the engineering team met subsequent to the operations standup with a visual management board that spanned projects on a time frame of weeks looking into the future. This allowed to resolve any items that required escalation from the operations meeting, and manage timelines of all ongoing projects to ensure on time delivery. The focus for engineering was primarily on 'winning the week' in terms of getting new builds prepared, while the time frame for sales and program management was on 'winning the month'.

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Chapter 5

Conclusion and Future Directions

Motivated by the challenging situation of the rapidly growing company Agouraprint, this work presents a data strategy to support the rapid growth and successful operation of an additive manufacturing company. The central idea is to connect a variety of data to the unit of a build – one unit of manufacturing in AM. Connecting commercial data, information about geometry, processing, materials, post-processing, and testing to their respective builds allows to gain a system-level understanding while also being able to drill deeper into details where needed.

Successful implementation of the described strategy heavily benefits from having good IT infrastructure such as ERP, MRP, and CRM systems, as well as an organizational culture that emphasizes quality of documentation. Critical components of a successful implementation, besides the mentioned infrastructure, are strong leadership, the ability to manage organizational transitions while upholding daily operations, as well as user training. After implementation, the framework can be used to (i) qualify processes and certify materials, (ii) improve quoting quality and efficiency, (iii) support engineering and R&D, (iv) derive critical operations KPIs such as *revenue per build*, *builds per week*, and *days per build*, which can be used for budgeting and capacity planning as well as business control, (v) make strategic decisions on capital expenses and headcount planning, as well as (iv) ensure traceability of materials and parts. Together, these applications support decision makers as well as commercial and technical staff in their work, both strategic as well as during day-to-day operations.

Longer term, the accumulation of structured data will become a valuable asset for a digital manufacturing company. A potential future use case of utilizing the information stored in the data warehouse is training machine learning algorithms for the purpose of (i) optimizing processing parameters, (ii) defect detection, (iii) designing novel materials, or also (iv) topology optimization during part design.

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