Skolkovo Institute of Science and Technology

INTEGRATED ENGINEERING AND MANUFACTURING CHANGE MANAGEMENT IN THE ADDITIVE MANUFACTURING CONTEXT

Doctoral Thesis

by

ELDAR SHAKIROV

DOCTORAL PROGRAM IN ENGINEERING SYSTEMS

Supervisor
Professor Ighor K. Uzhinsky
Skolkovo Institute of Science and Technology

Co-supervisor
Professor Clement Fortin
Skolkovo Institute of Science and Technology

Co-supervisor
Professor A. John Hart
Massachusetts Institute of Technology

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I hereby declare that the work presented in this thesis was carried out by myself at Skolkovo Institute of Science and Technology, Moscow, except where due acknowledgement is made, and has not been submitted for any other degree.

Eldar Shakirov
Supervisor Professor Ighor K. Uzhinsky
Co-supervisor Professor Clement Fortin

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Abstract

The product creation process involves various quantitative and qualitative decisions related to designing the product and the system executing its development and manufacturing operations. This comprehensive procedure includes many engineering and manufacturing disciplines interwoven by numerous technical, functional, and economic requirements. Currently, there is a challenge of providing an integrated perspective across the disciplines with an accurate quantitative evaluation of the case. Perhaps, changes to product or manufacturing process and system design demonstrate this most vividly: the whole system needs to be re-evaluated even if only one element is modified. Moreover, the introduction of innovative technologies further escalates competitiveness in product development (PD) endeavors. Additive manufacturing (AM) – a key component of the next era production paradigm – impacts the whole creation process and brings the domains of engineering and manufacturing even closer due to its digital nature.

Therefore, in planning change management, or PD activities in general, it is vital to make a comprehensive multidomain analysis considering the influence of AM. In this regard, there is a lack of tools that can quantitatively assess the time- and cost- implications of the decision options and facilitate selecting the best alternative.

This dissertation brings three contributions that collectively pursue closing the stated research gap. First, it elaborates the conception of integrated change management (ICM) by proposing the reference processes and highlighting the critical interconnections. Second, it reports the insights on AM impact obtained through an interview-based case study with a large energy sector manufacturer applying a metal printing technique to produce and maintain the functional components. Third, this work presents a simulation-based analytical framework enabling an integrated quantitative assessment of the engineering and manufacturing planning decisions, considering the AM context. Its capabilities have

been tested and validated on a realistic aerospace case study, quantifying the impact of various decisions on change lead time and cost.

This input is expected to empower the practitioners with a holistic view on the management of changes, thus improving the coordination and reducing resource expenditure within the PD projects. The AM context consideration further emphasizes this study's value as it underlines the benefits and difficulties in technology uptake. With the proposed framework, the company can improve the ICM process architecture by selecting the constituent steps and iteration patterns among them, leading to better process reliability and robustness. Also, it aids in configuring the manufacturing system in the number of machines and workers, lot sizing, shift mode, or layout design for the most efficient performance in terms of the techno-economic indicators significant for a given case. Altogether, the proposed perspectives and modeling capabilities can support the planning of PD and manufacturing operations and catalyze the adoption of AM.

In conclusion, the thesis discusses the utility, limitations, and challenges associated with the ICM concept, framework application, and its physical validation on a real case study. Finally, it gives an outlook for future research related to modeling the product creation activities and development of AM and the manufacturing workforce.

Author’s Publications

Shakirov, E., Kattner N., Fortin C., Uzhinsky I. and Lindemann U. (2021) ‘Reducing the Uncertainty in Engineering Change Management Using Historical Data and Simulation Modeling: a Process Twin Concept’, *International Journal of Product Lifecycle Management*.
doi: 10.1504/IJPLM.2021.10037271

Shakirov, E., Gee K., Quinlan H., Hart A.J., Fortin C. and Uzhinsky I. (2020) ‘Simulating the AM Production Facility: A Configurable Software Tool for Strategic Facility-Level Planning’. *Proceedings of the ASME 2020 15th International Manufacturing Science and Engineering Conference. Volume 2: Manufacturing Processes; Manufacturing Systems; Nano/Micro/Meso Manufacturing; Quality and Reliability. Virtual, Online. September 3, 2020. V002T07A014. ASME.*
doi: 10.1115/MSEC2020-8308.

Kattner, N., **Shakirov, E.** and Lindemann, U. (2019) ‘An Approach to Assess Engineering Change Effort Retrospectively Utilizing Past Engineering Change Information’, in Fortin, C. et al. (eds) *Product Lifecycle Management in the Digital Twin Era*. Cham: Springer International Publishing, pp. 223–232.
doi: 10.1007/978-3-030-42250-9_21.

Shakirov, E., Brandl F.J., Bauer H., Kattner N., Becerril L., Fortin C., Lindemann U., Reinhart G. and Uzhinsky I. (2019) ‘Integration of Engineering and Manufacturing Change Management: Infrastructure and Scenarios for Teaching and Demonstration’, in *52nd CIRP Conference on Manufacturing Systems (CMS), 2019, Procedia CIRP*, pp. 535–540.
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Moscow, July 7th, 2021

Eldar Shakirov

Preface

This dissertation is the result of the author's research efforts at the Skoltech laboratory of Cyber-Physical Systems (CPS) and collaboration with colleagues from the Technical University of Munich (TUM) and Massachusetts Institute of Technology (MIT).

The CPS laboratory investigates the methods of mechatronic systems' modeling, simulation, and analysis for various industrial applications. Leveraging the infrastructure for product lifecycle management (PLM), this research was able to explore the challenges at the intersection of product and manufacturing systems development through modeling and simulation.

During the research visit to the TUM Institute for Machine Tools and Industrial Management (*iwb*), the author has honed his focus on integrated change management. The extensive expertise of the colleagues from *iwb* and the Laboratory for Product Development and Lightweight Design (LPL) in engineering and manufacturing change management had a profound impact on this study.

Through the research visit to the MIT Industrial Performance Center (IPC) for the "Work of the Future" project – an institute-wide initiative exploring the transformation of work – the author has introduced the aspects of additive manufacturing (AM) impact on the product development and manufacturing practices. In collaboration with the MIT Mechanosynthesis group, the author has elaborated the simulation-based analysis of an AM-enabled product creation system. The group's expertise in AM and product development has significantly catalyzed the refinement of research questions and their consequent investigation.

During this whole study, the author has participated in various academic and industrial venues facilitating the exchange with researchers and practitioners working on related topics. They include the CIRP Conference on Manufacturing Systems 2019, the International Conference on Product Lifecycle Management 2019, the ASME Manufacturing Science and Engineering Conference 2020, PLM Europe 2017, Hannover Messe 2019, and Formnext 2019.

Contents

Chapter 1

Introduction to the additive manufacturing-enabled product creation process

This chapter introduces the major tendencies affecting product development (PD) and manufacturing, such as product lifecycle digitalization, model-based engineering (digital engineering), agile PD of hardware. It then transitions to the importance of engineering and manufacturing change management, which takes a significant portion of PD efforts. After that, it introduces an additive manufacturing context via current applications and the difficulty of enabling serial production with AM. It points to the lack of substantial research that explains how AM changes resource expenditure throughout the product lifecycle and engineering and manufacturing operations in particular. To study this issue quantitatively, we need an analytical framework that would consider the necessary factors and evaluate their influence. Finally, this section presents a specific research methodology for investigating the identified research gaps, which correlates with the design research methodology elaborated by Blessing and Chakrabarti (2009).

1.1 Product lifecycle in the Industry 4.0 context

The technological advancement of the modern world via ubiquitous digitalization creates the need for a better organization across the operational sectors and supply chains. Manufacturing, which takes about 15.4% of the worldwide gross domestic product (GDP), is no exception (*Manufacturing, value added (% of GDP) | Data*, 2019). To recognize the changes upcoming in the field, the German Academy of Science and Engineering was one of the first to introduce the Industrie 4.0 (i.e., Industry 4.0 in German) research agenda and proposed the implementation recommendations towards the fourth industrial revolution (*Industry 4.0 - BMBF*, 2011; Kagermann, Wahlster and Helbig, 2013). This concept's central component has many alternative names across the world, such as the Smart Factory, Smart Manufacturing, Smart Production, or Advanced Manufacturing (Kagermann, Wahlster and Helbig, 2013). Despite the terminological discrepancy, it can be seen that the essence of industry transformation lies in the aim to provide intelligence for the operations of supply chain processes, workforce, manufacturing system, and product. As shown in Figure 1.1, the base technologies for this are related to the Internet of Things (IoT), cloud technologies, Big Data, and analytics. Within this paradigm, there is a set of technologies aiming at various practical enhancements: firms vertical integration, processes virtualization and automation, data traceability, manufacturing flexibility, and energy management (Frank, Dalenogare and Ayala, 2019).

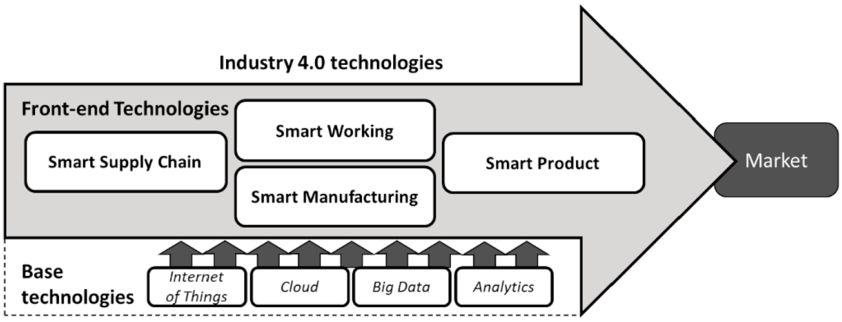

Figure 1.1. The theoretical framework of Industry 4.0 technologies by (Frank, Dalenogare and Ayala, 2019).

Though Industry 4.0 is applicable to both discrete and process manufacturing, in this work, we concentrate only on the context of producing the distinct, separate, physical units. In this regard, modern companies strive to extract as much benefit from their products during every stage of product lifecycle management (PLM), shown in Figure 1.2. This product- and service-centric strategy has five major stages encompassing research, product planning, development, production, marketing, operation, service, and utilization. Each step generates and uses the information about the product; therefore, it is critical to ensure specific integration and communication channels. For these purposes, the firms use the PLM systems that store the product data and link it to the associated employees and the data on corresponding manufacturing processes.

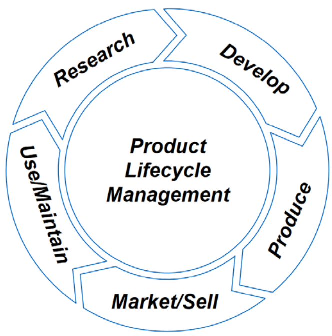

Figure 1.2. Stages of Product Lifecycle Management, adapted from (CIMdata, 2017).

Going further with the development of Industry 4.0 base technologies shown in Figure 1.1 and building upon the PLM model-based ecosystem, companies pursue the application of the digital twin (DT) concept. This comprehensive and challenging to realize idea provokes both academia and industry with the difficulty of creating applications across various industries. Barricelli, Casiraghi, and Fogli (2019) have identified 29 different DT definitions that can be grouped around six key points; DTs can be thought of as the solutions for integrating, cloning, linking, describing, predicting, or virtualizing the physical counterpart. Another recent study has generalized the DT definitions around three crucial characteristics: the virtual dynamic representation of the physical system, automatic and bidirectional exchange of data, and the coverage of an entire lifecycle and continuous connection to it (Trauer *et al.*, 2020). Comparing two basic definitions by Grieves and CIRP Encyclopedia of Production Engineering, other researchers have found that both concur in acknowledging the presence of physical and digital embodiments of the product (or product-service system) but differ in accounting for the virtual-to-physical connection between them (Jones *et al.*, 2020). Whereas Grieves's definition stresses the necessity of a bi-directional data connection, the CIRP Encyclopedia of Production Engineering distinguishes among three possible *"connectivity modes"* between the physical and digital counterparts.

Despite existing inconsistency in DT definitions, the perception of the general principle behind DT operation and its expected use cases along the product lifecycle are commonly recognized (Barricelli, Casiraghi and Fogli, 2019; Jones *et al.*, 2020; Trauer *et al.*, 2020). The interconnection of the physical and digital entities can be used at every stage of the product development (PD) and production processes to enhance the exploration of the solutions feasible region through modeling and simulations, and thus improve the system's performance. At the operations and service stage, DTs can be used to mitigate the system's undesirable emergent behavior by monitoring the current state and investigating the possible scenarios (Grieves and Vickers, 2017). However, on the way to this technology potential realization, it is necessary to overcome the challenges associated with (1) standardization and progression of data collection, transmission, and integration methods, (2) development of adequate analytical modeling frameworks, and (3) advancement of the interdisciplinary organizations with necessary skills and communication channels both within and between the companies (Tao and Qi, 2019). Furthermore, each of these restrictions is exacerbated with uncertainty due to natural variabilities in process parameters and inaccuracy in data measurement or physics-based laws formulation (Karve *et al.*, 2020). Still, several examples have already shown the applications across a few industries, with manufacturing, aviation, and healthcare leading the advancement (Barricelli, Casiraghi and Fogli, 2019). To date, most of the use cases are built on diverse digital representations of the cyber-physical systems, such as the multiphysical computational models or process surrogate models, and devoted to the enhancement of products or manufacturing systems performance characteristics. They are evidencing how modeling, simulation, and machine learning-based algorithms can be used in behavioral analysis and performance prediction for products or processes executed by them (Ríos *et al.*, 2015; Kritzinger *et al.*, 2018; Karve *et al.*, 2020; Trauer *et al.*, 2020).

Recognizing the challenges of adopting the Industry 4.0 technologies and the upward trend towards product personalization – which targets to bring more value, efficiency, and individualization to the product (Hu, 2013) – this work addresses the urgency of creating the responsive, agile, and cost-efficient engineering and manufacturing systems. Furthermore, this work believes that the cornerstone of such flexibility is an adept control of changes in design, engineering, and manufacturing, since “the entire product development process can be described as a continuous change management process” (Fricke *et al.*, 2000). According to previous studies, handling engineering changes can take up to 30-50% of the overall product development effort (Loch and Terwiesch, 1999; Fricke *et al.*, 2000). Also, reviewing the past studies, researchers indicate that the minimal cost of managing the engineering change takes €1,000-2,000, whereas the actual cost can reach several million EUR. Furthermore, on average, a company would deal with at least 500 manufacturing changes annually, which costs are in the same range (Koch, 2017). As the customer demand is becoming more personalized, companies would need to conduct even more engineering and manufacturing changes on their original products to execute the customized orders. Thus, the success of using the new technologies in responding to shifting consumer preferences is contingent upon the organizational elasticity of those engineering and manufacturing systems. A critical component of this challenge is structural complexity management, i.e., the simultaneous consideration of multiple aspects in product design. The internal company factors can originate from the product, process, or organizational complexity domains of the project (Lindemann, Maurer and Braun, 2009), and therefore require a comprehensive integrated study. Based on this, we formulate **the first research motivation (RM-1)** of this work:

RM-1 *Develop an approach to support practitioners in managing the engineering and manufacturing changes - happening during the product creation process - in an integrated manner.*

1.2 Additive Manufacturing context

Among the variety of advanced manufacturing topics, Additive Manufacturing (AM), also called 3D printing[1], is one that increasingly attracts the high attention of the research and industry communities over the recent years. Between 2015 and 2019, both the number of publications on AM indexed in Scopus and the number of visitors of the leading global AM trade fair Formnext has almost quadrupled, as shown in Figure 1.3 and Figure 1.4.

To date, the world has already evidenced AM applications at four out of five stages of AM adoption proposed by Hart and Quinlan (2019). At the (I) *Early Stage*, AM enables prototyping of the product concepts. Figure 1.5a demonstrates PepsiCo’s example of 3D printing the non-eatable potato chips for studying the product ergonomics with their customers, in which the company – according to their senior R&D director – has shortened the design definition cycle from 12-18 to 3 months (*PepsiCo Using 3D Printing to Design Bigger, Bolder Potato Chips - YouTube*, 2015).

[1] Alternative terms for AM can include: Additive Fabrication, Additive Layer Manufacturing, Solid Freeform Fabrication, Rapid Manufacturing, Rapid Prototyping, Rapid Tooling, Direct Digital Manufacturing.

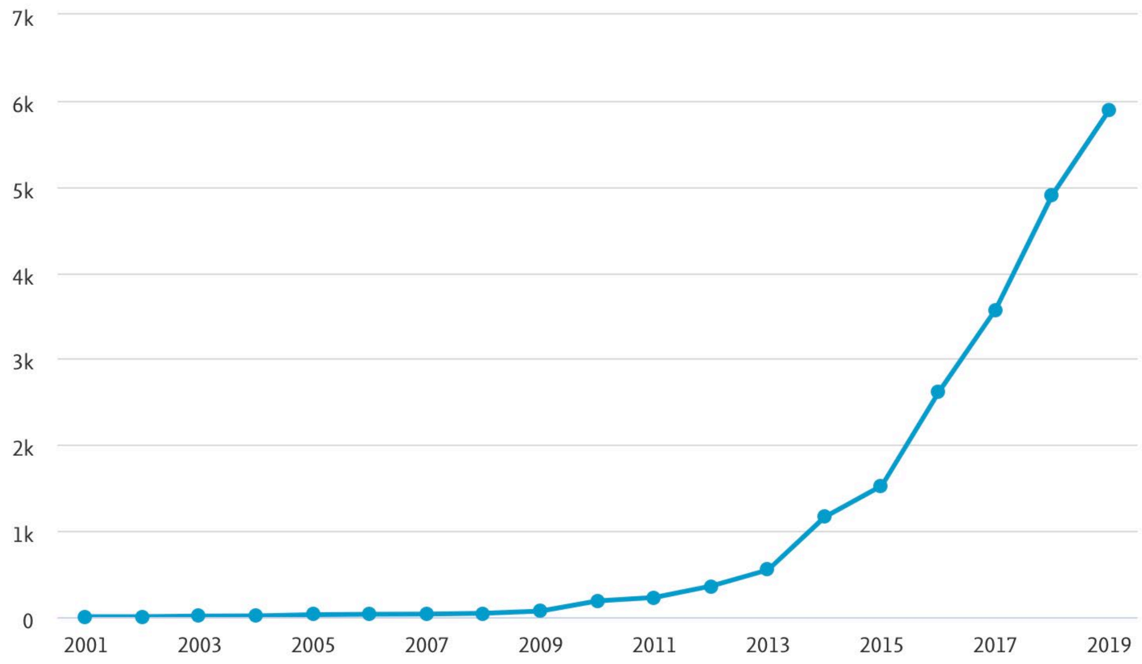

Figure 1.3. The number of academic publications including the "additive manufacturing" keyword, Scopus (accessed on August 10, 2020).

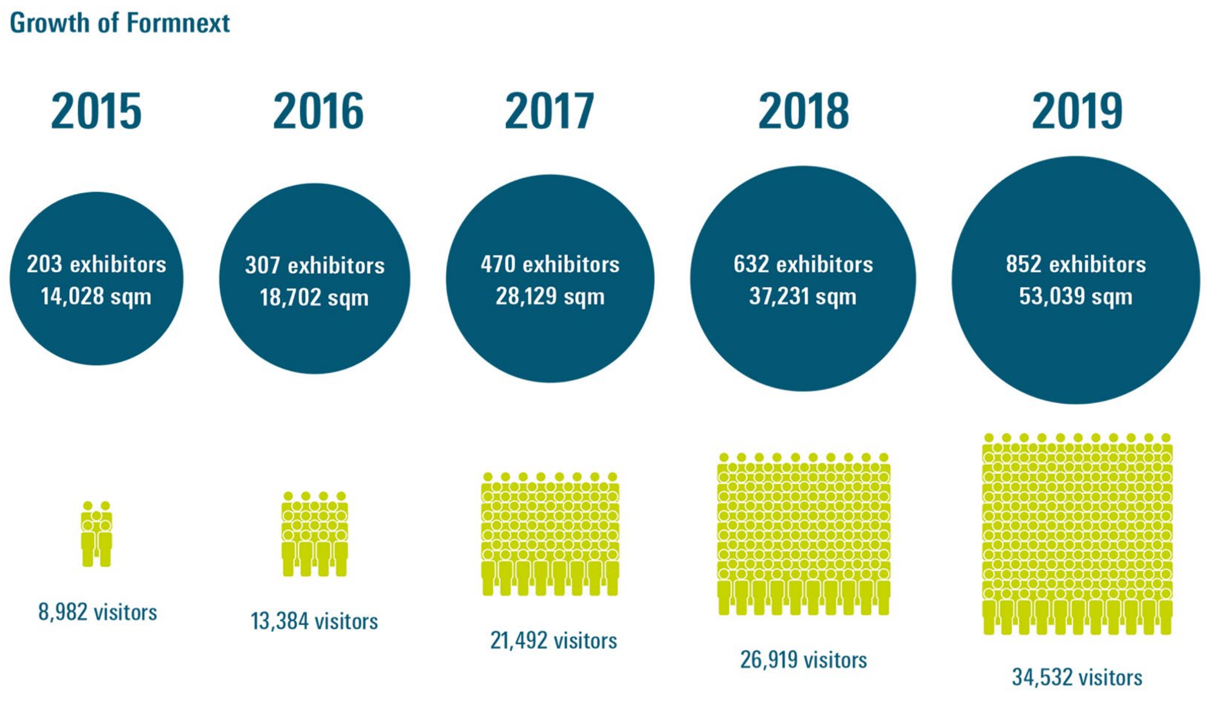

Figure 1.4. Statistics on the number of exhibitors and participants of Formnext (*Facts & figures - Formnext - Mesago*, 2019).

The second stage (II), *AM-Accelerated Product Development*, extends the application of AM from concept to functional prototyping. Therefore it expedites the PD process; Figure 1.5b shows the same-day design iterations out of Draft Resin material by Formlabs (presented at Formnext 2019).

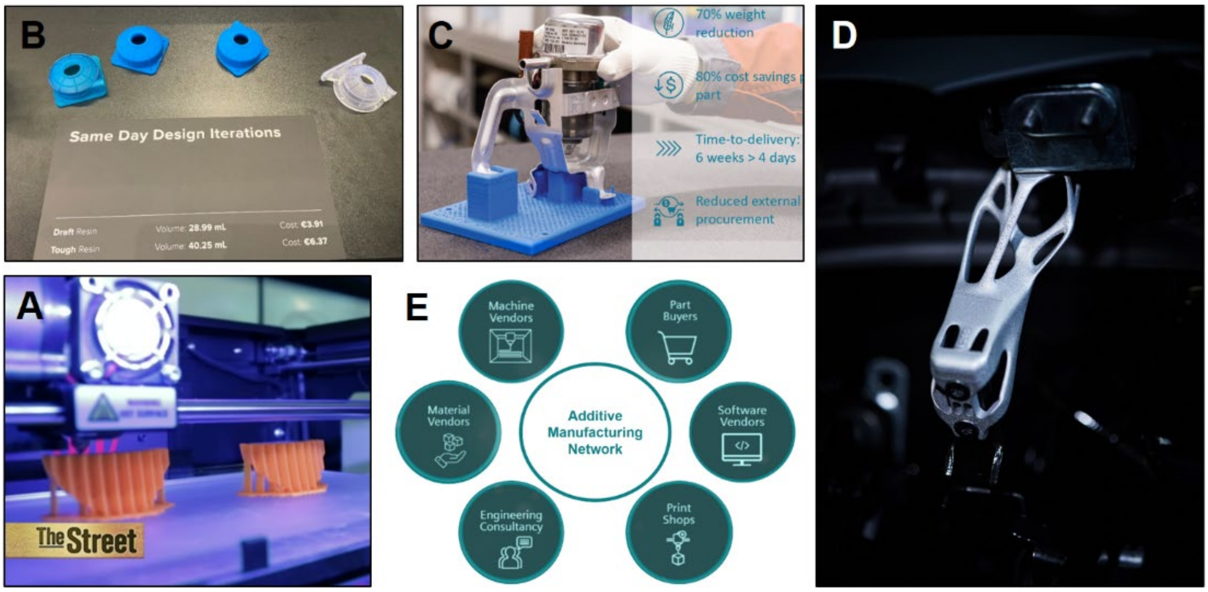

Figure 1.5. AM applications: (a) Potato chips prototyping[2]; (b) rapid functional prototyping; (c) 3D printed tooling for supporting the manufacturing process[3]; (d) serial production of end-use components[4]; (e) enabling the AM network[5].

The third (III) *AM Enhanced Production* stage designates the company's capability to exploit the technology in supporting its production operations; e.g., see the 3D printed assembly fixture application by Audi Sports that has drastically reduced the production costs and lead times (Figure 1.5c). At the fourth stage (IV) of technology adoption, *AM-Enabled Product*, the company indicates high capability – i.e., an ability to recognize and exploit the value of the technology – and organizational capacity to deploy AM applications and industrialize the technology. Figure 1.5d showcases the folding mechanism's bracket in BMW i8 Roadster that has proved a cost-effective series production with metal AM.

The fifth stage (V) of mastery over AM, *The Digital Business,* requires the robust digital thread along the entire product lifecycle. Though this vision has not yet been evidenced in full, some parts of it, along with the given above instances, already exist. Figure 1.5e refers to an example of the "Additive Manufacturing Network" by Siemens, which connects the customers with the providers, operators, and maintainers of the manufacturing resources, i.e., machinery, materials, and software. The idea's essence

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[2] Figure (a) source: (*PepsiCo Using 3D Printing to Design Bigger, Bolder Potato Chips - YouTube*, 2015).

[3] Figure (d) source: Audi Sports' presentation at Formnext TCT Conference 2019.

[4] Figure (c) source: (*The Ultimate Printing Machine - How BMW is applying 3D printing to commercial vehicles - TCT Magazine*, 2018).

[5] Figure (e) is adapted from the Siemens presentation on "Additive Manufacturing Network im Mittelstand" (2019). Available at: https://www.plm.automation.siemens.com/media/global/de/Additive%20Manufacturing%20Network%20im%20Mittelstand_tcm53-58282.pdf.

is to create an agile and far-reaching distributed manufacturing system that will use AM's digital nature and buttress the product creation and service activities with an on-demand supply of spare parts at the necessary location around the globe. In supporting the latter stages, AM also provides novel capabilities in product service and maintenance. An illustrative case study on the burner tip repair presented by Siemens reveals a good potential for sustainability advantage by AM (Andersson *et al.*, 2017; Walachowicz *et al.*, 2017). The further automation of the applications alike will require suitable hybrid machine tools, e.g., allowing the milling and consequent repairing of the damaged parts using the 3D printing methods[6].

These advancements have been possible because AM overcomes many geometric and material constraints existing for the parts made with traditional subtractive and formative manufacturing techniques. Unlike the well-established processes as milling, stamping, or casting, AM is building the parts layer by layer following the instructions of the computer numerical control (CNC) systems generated for the particular 3D model, as shown in Figure 1.6. Moreover, AM processes do not need custom tooling for printing the parts, and thus only digital data and feedstock material are necessary for operation. Testing the popular hypothesis of AM providing "complexity for free," researchers have compared selective laser melting (SLM) to CNC machining in terms of cost change when producing the parts of increasing complexity within the same bounding box. They have found that AM can provide even a downward cost trend, presumably due to reduced material usage and, hence, build time (Quinlan *et al.*, 2017).

Figure 1.6. Additive manufacturing layer by layer principle, adapted from (Lang *et al.*, 2019).

In general, three domains can characterize the space of components manufacturability from a market perspective, as shown in Figure 1.7: complexity, production volume, and customization. For manufacturing systems to provide commensurate agility in producing the personalized products in a given volume, they need to possess a chosen set of "ilities" (de Weck, Roos and Magee, 2011), such as evolvability, adjustability, scalability, or modularity, enabling the changeability of the system

[6] One reference of a single machine combining the conventional and additive methods to repair the damaged parts is the Lasertec 3D hybrid by DMG Mori (*End-to-End Competence – Maintenance, repair and manufacturing of large components.*, 2019). The machine can consequently conduct the operations of milling and laser deposition welding on the components as large as ø1,250x745 mm in size and 2,000 kg in mass.

(Wiendahl *et al.*, 2007). Due to its intrinsic properties mentioned above, AM advances many ilities and pushes the boundaries defined by the traditional methods along the complexity and customization axes. This way, AM puts an accent on the other manufacturing paradigms not considered thoroughly from a conventional manufacturing viewpoint, such as those discussed by Koren (2010) and Andersen *et al.* (2017).

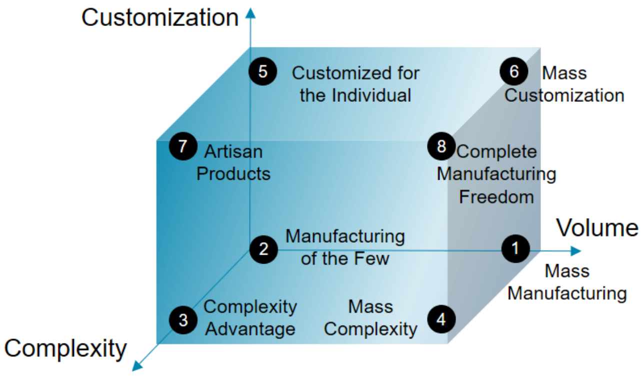

Figure 1.7. Complete manufacturing freedom space, adapted from (Conner *et al.*, 2014).

The previous set of paradigms has characterized the manufacturing system performance through the tradeoff in production volume and parts variety. By significantly enhancing the ability to customize the products and unlocking new levels of their geometrical complexity, AM allows looking at manufacturing from many new perspectives. AM potential helps us split the product variety aspect into product customization and complexity and, thus, complements the vision with consideration of a broader spectrum of paradigms, such as shown with alternatives 1-8 in Figure 1.7. Therefore, it extends the conventional space to unavailable before regions, promising to satisfy the complete manufacturing freedom requirements (Conner *et al.*, 2014). This argumentation and the described above examples of AM-enabled product and service opportunities make us think of the upcoming transformations in every stage of the product lifecycle. Especially, touching back the structural complexity of handling engineering and manufacturing changes, AM might bring essential and promising alterations into associated processes in terms of their cost and execution time.

However, despite a noticeable growth of the AM's market throughout the last decade illustrated in Figure 1.8, its fraction in overall manufacturing's GDP is still tiny, and the technology seems only to approach its inflection point: \$9.79B AM market[7] took only 0.07% of the overall \$13.3T worldwide

[7] As of the year 2020, the Wohlers Associates, Inc., estimates the AM industry to \$12.8B, designating a 7.5% annual growth indicating a significant deceleration from the average 27.4% growth over the previous decade, supposedly, as a result of the pandemic crisis (Metal Additive Manufacturing, 2021).

manufacturing GDP in 2018[8] (Quinlan, Gee and Shakirov, 2019). Presumably, the current state of technology readiness is still insufficient to fully capture the right side of the manufacturing freedom space (Figure 1.7) and enable the medium- and high-volume production of functional end-use parts. Though there is some evidence of the fourth adoption stage, its principle implementation strategy has not been formulated yet due to the difficulty of creating cost-efficient AM applications within stages (IV) and (V).

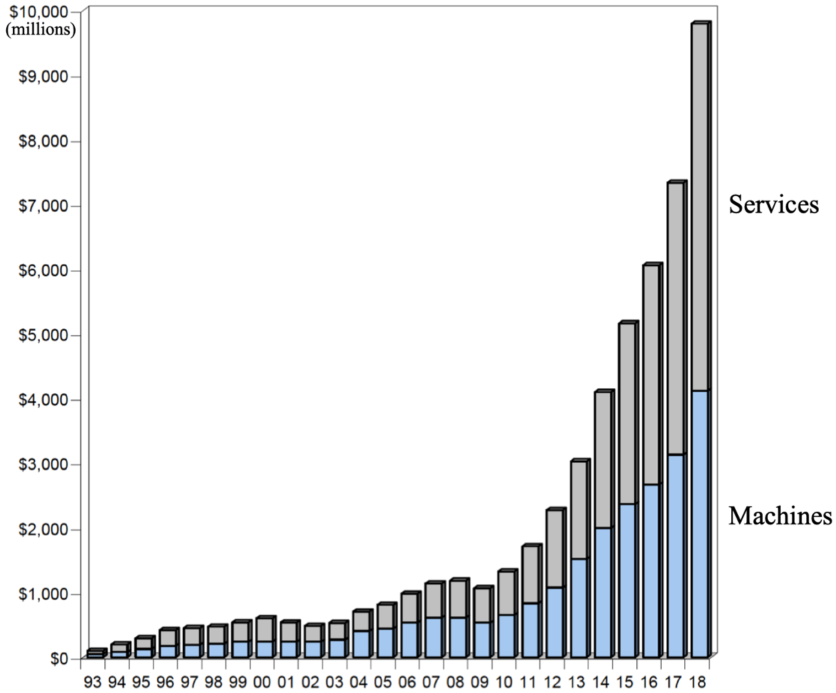

Figure 1.8. AM market in the 1993-2018 period (Wohlers *et al.*, 2019).

According to the BMW's presentation at Formnext TCT conference 2019, nowadays, a broader AM adoption in industrial production is limited by its cost: Figure 1.9 shows that the cost-effective range of applying laser powder-based fusion with aluminum lies in the €0.2-0.4 per ccm interval, whereas today's capabilities provide the cost of €1-4 per ccm. The company argues that decreasing the cost tenfold requires the new generation of AM systems. In this regard, there is still a lack of the methodical approaches for AM implementation given limited access to numerically evaluate different scenarios or precisely define the technology scale-up objectives. However, having such an ability would allow the practitioners to identify the existing limitations in AM industrialization and develop the corresponding solutions.

[8] AM market data from (Wohlers *et al.*, 2019), manufacturing value added (%) from (*Manufacturing, value added (% of GDP) | Data*, 2019), worldwide GDP from (*GDP (current US$) | Data*, 2019).

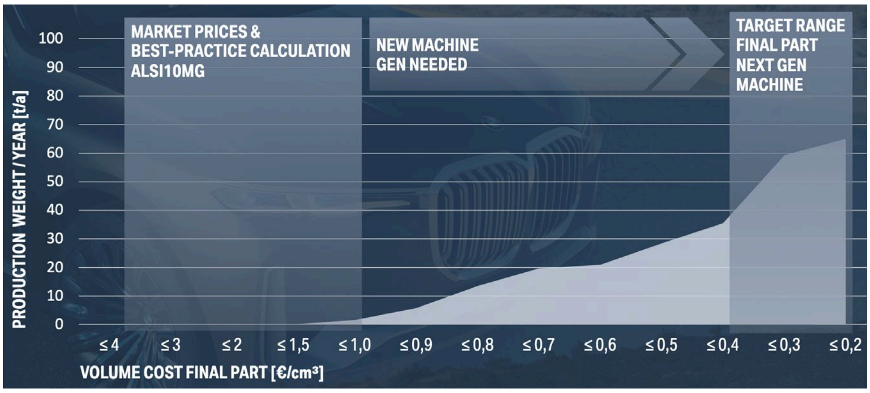

Figure 1.9. Production demand (tons per year) versus volume cost (EUR per ccm) feasibility range for laser powder-based fusion AM technology[9].

Building on AM's potential to transform the conventional methods to design, engineering, and manufacturing the products, and recognizing the challenge to advance the technology to the next stages of implementation globally, we formulate **the second research motivation (RM-2)**:

RM-2 *Provide the means to foster AM's industrialization and analyze the corresponding implications for the existing design, engineering, and manufacturing practices.*

By merging the stated research motivations (RM1 and RM2), we see a need to conduct a combined study on integrated management of engineering and manufacturing changes along with the measurable analysis of already existing and upcoming implications of AM industrialization. Out of this, we formulate the **global research objective (GRO)** of the dissertation:

GRO *Develop an approach for quantitative assessment of AM influence on the product creation process that will support the improvement of engineering and manufacturing change management.*

1.3 Research methodology and thesis structure

The research methodology used in this work significantly correlates with the Design Research Methodology (DRM) steps discussed by Blessing and Chakrabarti (2009). The DRM methodological framework suggests four stages to streamline the research efficiency: a research clarification, a descriptive study I, a prescriptive study, and a descriptive study II. The project goes through the formulation of the research questions and objectives, their refinement via literature review, solution development, empirical studies execution, and results evaluation. Below is an explanation of the thesis structure mapped to the DRM methodology stages.

[9] Retrieved from the BMW Group's presentation at Formnext TCT Conference 2019.

Research clarification (RC). This research stage has started with the global research objective (GRO) definition: based on an initial literature review, we have identified two research motivations that resulted in the GRO (Chapter 1). Further, through a more comprehensive literature review, this stage defines the ground hypotheses and relevant topics of study, identifies the success factors for GRO implementation, and formulates the research gaps RG-1 – RG-3, research objectives RO-1 – RO-3, research question RQ, and sub-questions RSQ-1.1 – RSQ-3.2 (Chapter 2).

Descriptive study I (DS-I). To develop a sufficient understanding of the research topic, this work first conducts the review-based DS-I on the defined research sub-questions RSQ-1.1 – RSQ-1.3 (section 3.1). Then it fulfills an identified need for the exploratory and descriptive empirical study on RSQ-2.1 by conducting a series of in-depth semi-structured interviews with the leading AM adopters (section 3.2).

Prescriptive study (PS). This stage determines the key factors necessary to eliminate the research gaps identified in RC and refined in DS-I. It answers the sub-questions RSQ-1.4 – RSQ-1.5 and RSQ-2.2 – RSQ-2.4 by executing the comprehensive PS, which first provides the set of taken assumptions, the description of the developed supporting techniques, and the steps taken to create it (sections 4.1-4.2). Then, it explains the logic of an integrated solution and prescribes its concept of operations (section 4.3), hence addressing the sub-question RSQ-3.1.

Descriptive study II (DS-II). The concluding DS-II stage demonstrates the application of the developed set of techniques on a realistic use case and thus fulfills the stated research objectives RO-1 – RO-3 (Chapter 5). Then, it evaluates the solution and discusses its potential impact, addressing the sub-question RSQ-3.2. DS-II collects the evaluation results, processes them, and sets the stage for their critical analysis. Based on that, this work derives the implications of using the solution, assesses its reliability, the corresponding advantages and limitations, and proposes further research and development prospects (Chapter 6).

Table 1.1 maps the adopted methodology on the content of the thesis.

Table 1.1. Mapping the DRM stages on the thesis structure.

Thesis chapter	Purpose and output	DRM stage
1. Introduction to the additive manufacturing-enabled product creation process.	Overview of the literature and formulation of the research motivations and global objective.	RC
2. Integrated change management and the role of additive manufacturing.	Identification of the research gaps based on the comprehensive literature review on engineering and manufacturing change management and on additive manufacturing. Formulation of the research objectives and questions.	
3. Developing an understanding of integrated change management in the Additive Manufacturing context.	Literature-based definition of integrated change management and highlighting of the critical interdomain connections. Interview-based analysis of additive manufacturing's impact on the product creation process and integrated change management.	DS-I
4. Model-based analytical framework: evaluating the cost and times of the integrated change management process.	Development of an analytical framework for evaluation of product development operations. Development of an analytical framework for techno-economic evaluation of manufacturing operations. Integration of the models into a single framework.	PS
5. Framework use case and validation.	Application and validation of the developed framework.	DS-II
6. Discussion and Conclusions.	Evaluation of the developed framework.	

Chapter 2

Integrated change management and the role of additive manufacturing

This chapter provides the literature review on handling engineering and manufacturing changes in an AM-enabled product creation environment. However, it seems that so far, the question of AM influence on engineering or manufacturing change management has not been covered in any published academic effort. For example, a query *“("engineering change" or "engineering change management" or "manufacturing change" or "manufacturing change management") and ("additive manufacturing" or "3D printing")*” in the Scopus database does not give any relevant results[10]. Therefore, the chapter begins with the literature review on the product creation steps and gives the basic definitions. It then focuses on engineering change management by explaining its purpose, practices, and ways to improve it. Then, it concentrates on an adjacent topic - manufacturing change management – in which it points at the importance of manufacturing operations and their costs, as that they also can be a source of changes for product design (Koch, 2017). Further, it stresses the criticality of an integrated approach in the execution and coordination of engineering and manufacturing changes.

The second part of this chapter starts with reviewing the additive manufacturing technologies and their cumulative potential to influence product development (PD) and production practices. It then focuses on those based on metals powder-bed fusion as on ones of today’s most promising industrialization techniques (Schmidt *et al.*, 2017). Then, it reviews the progress in serial AM by giving the industrial examples, concluding that there is a difficulty to scale-up the technology. Though it gets clear that AM would significantly affect engineering and manufacturing change management operations, the essential elements of the transformation process must be thoroughly studied. For this, we review research on quantitative assessment of the product development and manufacturing processes. Furthermore, examining prior work related to the integrated analysis of the PD and manufacturing operations, this chapter deduces a lack of corresponding model-based tools producing the quantitative evaluation. At this point, we refine the problem statement along with the research questions and set the stage for the empirical study of this work.

[10] Accessed on August 13, 2020.

2.1 Integrated change management as the cornerstone of the effective product creation process

Product creation is a complex and multidisciplinary process that aims to identify the customer needs and produce a tangible system satisfying those needs. It involves the stakeholders within and outside an enterprise, contributing to product marketing, design, and manufacturing. According to Ulrich and Eppinger (2011), its success can be measured in five dimensions: product quality, product cost, development time, development cost, and development capability. Here we can assume that these are first-order indicators displaying the company's market competitiveness, whereas additional related metrics consistent with the company's strategic vision are second-order, such as sustainability or diversity, equity, and inclusion. To attain the desired outcome in any dimension, an enterprise strives to make well-versed decisions during all phases of the product development (PD) process, which include: product planning, concept development, system-level design, detail design, testing and refinement, production planning, and production ramp-up (Krishnan and Ulrich, 2001; Pahl *et al.*, 2007; Ulrich and Eppinger, 2011).

As shown in Figure 1.1, each phase contributes to the project cost, and according to Defense Acquisition University's statistical analysis on past projects in the US DoD, about 75% of the total project cost is already committed at the product design stage.

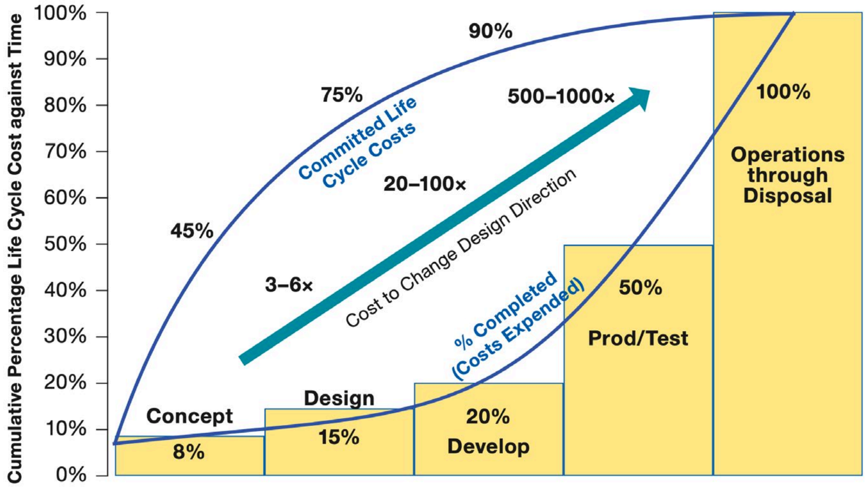

Figure 2.1. Committed project life cycle costs versus expended costs along the project phases; retrieved from (Library and Administration, 2017), adapted from the original by Defense Acquisition University.

Furthermore, based on the Costs Expended curve in Figure 2.1 and the resulting cash flow curves in Figure 2.2, we see that major expenses happen with production initiation; this also means that the design decisions play a critical role in defining the manufacturing costs, and thus greatly impact – directly and indirectly – the overall project cost. This relationship dictates a crucial need for close cooperative work across the design, engineering, and manufacturing stages, as the former defines the latter's cost. Particularly, an understanding of the quantitative dependencies between the costs and lead times of different phases of the product creation process is necessary to schedule the projects better and minimize the expenditures. Therefore, this work sees the importance of developing the instruments to support an integrated analysis of engineering and manufacturing planning decisions.

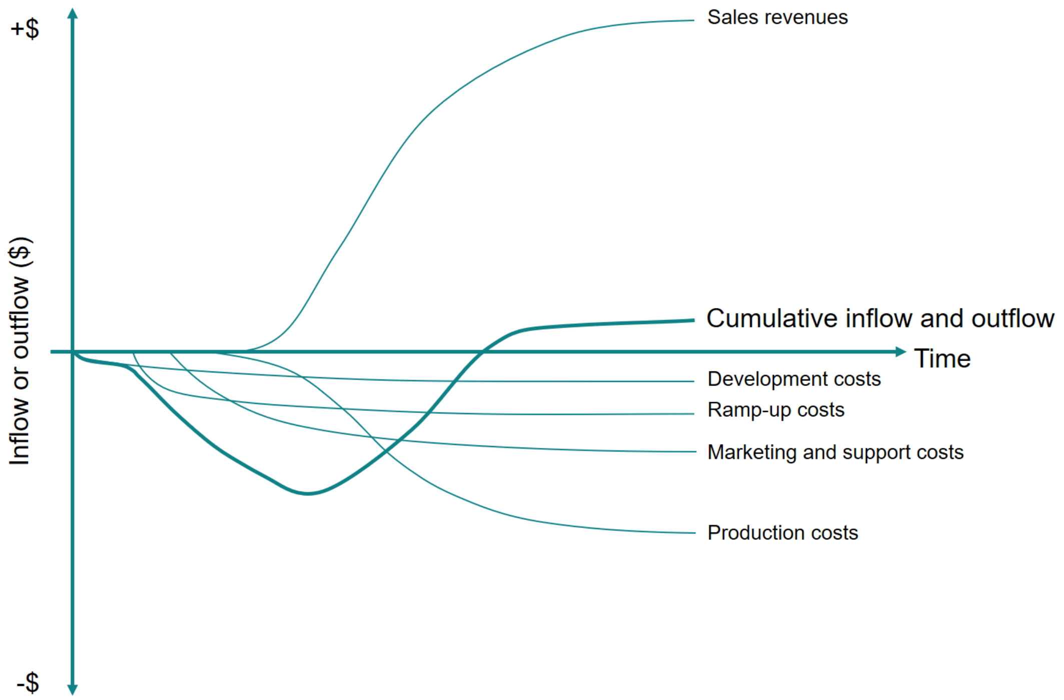

Figure 2.2. Typical PD project cash flow, adapted from (Ulrich and Eppinger, 2011).

2.1.1 Integrating engineering and manufacturing operations

Addressing the need for closer internal cooperation, the PD community came up with the concurrent engineering (CE) approach, also known as simultaneous engineering. It aims to reduce the project time and expenditure of induced resources by standardizing, parallelizing, and integrating the internal PD activities (Bullinger and Warschat, 1996). One of the main ideas behind it is to execute the design operations, i.e., the major expenditure committers, concurrently with the manufacturing planning operations, i.e., the major expenditures (Stjepandic, Wognum and Verhagen, 2015). Researchers underline that to enable the CE method, the company needs to establish a multidisciplinary integrated product team (IPT); to that end, it is crucial to provide efficient communication channels supporting successful cross-team operation (Fortin and Huet, 2007).

At the managerial level, researchers have discussed various methods and needs for facilitating the integrated PD process. Ettlie (1995) has surveyed 43 discrete manufacturing firms to test the hypotheses on integrated product-process development. Out of that, it has been found that the companies adopting an integrated development practice are more successful in terms of sales per employee. Though the author did not observe a reduction in project lead times in such companies – presumably, because of a still low level of approach adoption at that time – a significant positive correlation has been found between the company's size and its length of the development periods. These findings support the need for assistance in enabling integrated engineering-manufacturing decision-making entirely.

Further, Swink (1999) underlines the importance of manufacturability consideration for any new PD project's success and notes that prior literature does not give proper consideration to that. To investigate the effects of PD team integration, the author surveys the influence of PD factors (e.g., project scope, product newness) on product manufacturability success. One of the conclusions is that the project complexity and design outsourcing raise the manufacturing difficulty. Yet, if the team is adequately integrated, it can overcome those barriers.

However, the quality of team integration should be addressed not only at the managerial but also at the operational level. It is necessary to develop an integrated data structure, which would connect the elements of the product, organizational (people and resources), and process (business and operational workflows) domains (Lindemann, Maurer and Braun, 2009). The product data is generated throughout a whole product life cycle and thus managed by the PLM systems; it contains the information on product requirements, design, engineering analysis and testing results, etc. The data from an organizational domain includes and builds on the manufacturing system's architecture and the hierarchy of people involved; it is managed by such systems as the manufacturing execution system (MES), enterprise resource planning (ERP), and PLM systems. The process domain includes all the descriptions and documents associated with all the workflows involved in the PD and manufacturing processes; these are managed by the ERP, PLM, and MES systems in integration.

One significant contribution to connecting the product and manufacturing data has been made by introducing a Manufacturing Process Management (MPM) system. It provides an interactive analytics platform enabling unrestricted manipulation with a complete product information envelope. MPM augments workers' capabilities in defining the detailed manufacturing process with their interpretation of the product bill of materials (BOM) as the mBOM, i.e., manufacturing BOM (Gagné and Fortin, 2007). It creates vital visibility of product transformation along the PD process and facilitates cooperation among the departments, without which a company would lose efficiency operating with two distinct design databases called "As-Designed" and "As-Built" (Freedman, 1999). Therefore, the company needs to make sure that a proper connection between an MPM solution and the Product Data Management (PDM) system is in place so that an emerging engineering change would be reflected in a manufacturing change, and vice versa (Fortin and Huet, 2007). Such an integrated environment would help sustain the depth of numerous inter-domain linkages that shall be maintained throughout the change management routines, such as in the CMII configuration management model examined by Gagné and Fortin (2007).

Other researchers have supported an idea of a framework for ERP-PDM integration that would bring together the corresponding data on the product, process, and resources (PPR) and enhance configuration changes tracking. They have proposed to enable a context-specific transformation of the engineering BOM (eBOM) into the mBOM, which is essential for an ongoing globalization trend (Lee, Leem and Hwang, 2011). Extending this further, a co-evolution paradigm stresses the need to integrate the modifications in product or process domains with those of the production system architecture, i.e., manufacturing resources domain, and consider each during configurations (Tolio *et al.*, 2010). However, a possible challenge of such concurrent and, therefore, iterative processes is related to project maturation and increasing need for documentation that eventually slows the overall process and engineering change management in particular (Schuh *et al.*, 2017).

Collectively, the studies discuss CE and associated integration of engineering and manufacturing domains and outline a vital role for engineering change management, recognizing the importance of establishing the corresponding efficient workflows and data management systems. Therefore, the following section reviews the associated definitions, principal workflows, and state-of-the-art in advancing the engineering change management practice.

2.1.2 Engineering change management (ECM)

The tasks of PD projects can follow one of three design problem types: *original* design, for creating new solution principles via new technology invention or combination of known principles; *adaptive* design, to accommodate the established solution principles in a changed context; and *variant* design, where the design variables change within foreseen and specified limits (Pahl *et al.*, 2007). Especially in the cases of original and adaptive projects, PD processes continuously cope with novelty and rising complexity, evolving due to the introduction of new design issues and technologies, and thus pass uncertainty to constituting design and engineering activities, inducing their iterative nature (Eckert and Clarkson, 2010; Wynn and Clarkson, 2018). Responding to this, as if by conquering Everest, the engineering teams make the steps via the engineering change projects, thereby moving from one secure position to another. According to (Hamraz, Caldwell and Clarkson, 2013), the *engineering changes* (EC) are "*changes and/or modifications to released structure (fits, forms and dimensions, surfaces, materials etc.), behavior (stability, strength, corrosion etc.), function (speed, performance, efficiency, etc.), or the relations between functions and behavior (design principles), or behavior and structure (physical laws) of a technical artefact.*" This definition is built upon a set of prior versions – including the variations for such EC terminological alternatives as *product change*, *design change*, *engineering design change*, or *change* – and therefore considered to be the most precise produced so far, as it encompasses the pivotal components of the preceding definitions.

The PD project can trigger an EC for various reasons that we can group into two classes: *emergent*, i.e., originated by the product itself, and *initiated*, provoked outside the product by the involved stakeholders (Eckert, Clarkson and Zanker, 2004; Clarkson and Eckert, 2005).

Emergent causes include such cases as:

- Error correction (e.g., in design, testing, prototyping, or manufacturing);
- Safety assurance;
- Change of function;
- Quality assurance.

Initiated changes can be triggered by:

- Customers (e.g., requirement change);
- Sales and marketing;
- Product maintenance department;
- Production;
- Suppliers;
- Management;
- Regulators.

ECs can also differ in terms of execution urgency, as *immediate*, *mandatory*, and *convenience*, and also by timing, i.e., criticality: *early* (low impact), *mid-production* (with considerable potential impact to long-lead production), and *late* that can be ruinous to project schedule (Jarratt *et al.*, 2011).

In prior studies, researchers have found that projects' work related to EC can take around 30% of the overall PD effort (Jarratt *et al.*, 2011). Wasmer, Staub, and Vroom (2011) report that a typical cost of a change is measured in tens of thousands of USD and that the companies can go through hundreds of thousands ECs per year. Undoubtedly, the factual EC effort fractions differ from project to project and can be either small, in case of early insignificant changes, or large, when critical changes are conducted at the latter stages of the project. This degree of change depends on the resulting propagation of change, i.e., the extent to which one change can affect the overall product-process-organization system and trigger other changes. If the company could quantify this, it would have a better perception of the total effort necessary for an upcoming change. Therefore, researchers have dedicated numerous projects to developing the change propagation models, such as by Clarkson, Simons, and Eckert (2004), Hamraz, Caldwell, and Clarkson (2012), Koh, Caldwell, and Clarkson (2012), Pasqual and de Weck (2012). The tools created therein allow the user to systematically assess the change effects within either domain (product, process, and organization, i.e., social) or across several domains and plan project resources accordingly.

Furthermore, the efficiency of conducting the change depends on the company's formal procedure to it. The process of ECs organization, control, and execution is called *engineering change management*[11] (ECM) and covers a whole change lifecycle, from concept selection to manufacturing implementation and solution support (Hamraz, Caldwell and Clarkson, 2013). Such processes are usually represented via a standardized workflow – a reference process – that guides an engineering team along the EC. However, before deriving a company- and case-specific ECM reference process, it is important to recognize the principal aspects of PD processes characterization.

In contrast to many business and manufacturing processes created to execute the same tasks repeatedly, design and engineering usually perform unique assignments every time. Therefore, PD processes are better represented as the networks and not chains since they have more complicated dependencies and tend to be parallelized, as in concurrent engineering. Addressing this, (Browning, Fricke and Negele, 2006) emphasize the need to depict PD processes – such as the ECM reference processes – through a combination of descriptive and prescriptive models. This way, it would incorporate tacit knowledge synthesized in descriptive representations and prescriptive instructions that rely on past projects' standards and documentations. Since it is dangerous to have solely prescriptive rigid reference processes for the PD workflows, "*having a shared, agreed-to representation of an approach and a network of commitments that is known to have worked in a somewhat similar situation is an invaluable aid to project planning and execution*" (Browning, Fricke and Negele, 2006).

Researchers have conducted literature reviews, case studies, interviews, and workshops with industry experts on the lookout for the necessary structure and workflow elements of an effective prescriptive ECM process representation. Jarratt, Clarkson, and Eckert (2005) present a high-level process encompassing preceding literature's ideas. As shown in the top row of Figure 2.3, such a process consists of six phases, going from the change request through solutions development and implementation to review of change efficacy. Also, this process accounts for two explicit possibilities of rework loops. The first iteration can happen after the risk assessment step: if the previously identified solution is too unsafe, the process returns to the previous stage to identify other solutions. The second source of iteration is in the decision stage, i.e., where the Engineering Change Board can request additional risk analysis before approving or disapproving the change request. The authors note that at a close examination of a case-adjusted reference process, one can notice the difference in its focus.

[11] As pointed by Jarratt, Clarkson, and Eckert (2005), one shall not confuse *engineering change* with the general *change management* concept common in management and business literature. *Engineering change* refers to the product changes, whereas *change management* concerns with the organizational transformations that the company needs to go through when introducing new business processes, for example.

Depending on the product, companies may have a more serious concern towards either safety, cost, quality, or project lead time.

Following this, another work towards standardization of the ECM reference process has been conducted by the Strategic Automotive product data Standards Industry Group (SASIG). It has been done via cooperation between the international automotive associations, such as the German Association of the Automotive Industry, Automotive Industry Action Group (U.S.), Japan Automobile Manufacturers Association, and others (VDA 4965, 2010c). Their ECM Recommendation represents the guideline for cross-company EC implementation by providing the set of workflows, data models, relevant terms, definitions, and standards necessary to conduct the coordinated product-related changes with respect to engineering and manufacturing tasks. It captures a similar scope and iteration possibilities as in (Jarratt, Clarkson and Eckert, 2005), however, excluding the reviewing stage but providing a deep elaboration on the Engineering Change Request (ECR), Engineering Change Order (ECO), and the associated lower-level workflows and data models in (VDA 4965, 2010a, 2010b). Figure 2.3 shows its major stages; additionally, Figure 2.4 gives a more detailed view of the SASIG five-step ECM process in the IDEF0 format. By following this and associated lower-level workflows considering possible roles, activities, and interrelations, by defining the interaction scenarios with the suppliers, and building a common approach for ensuring geometrical, functional, and manufacturing-related requirements, the company can come up with its custom reference process for effective coordination of the ECs. It is important to note that the reports and articles accompanying that project have also addressed the difficulty of cross-organizational coordination in the ECM projects: Wasmer, Staub, and Vroom (2011) elaborate on the related challenges and suggest the ways to overcome them. Since the ECM process, in many cases, is a cross-company effort, an integrated solution to information management must provide the means to minimize data translation when it is passing the company borders.

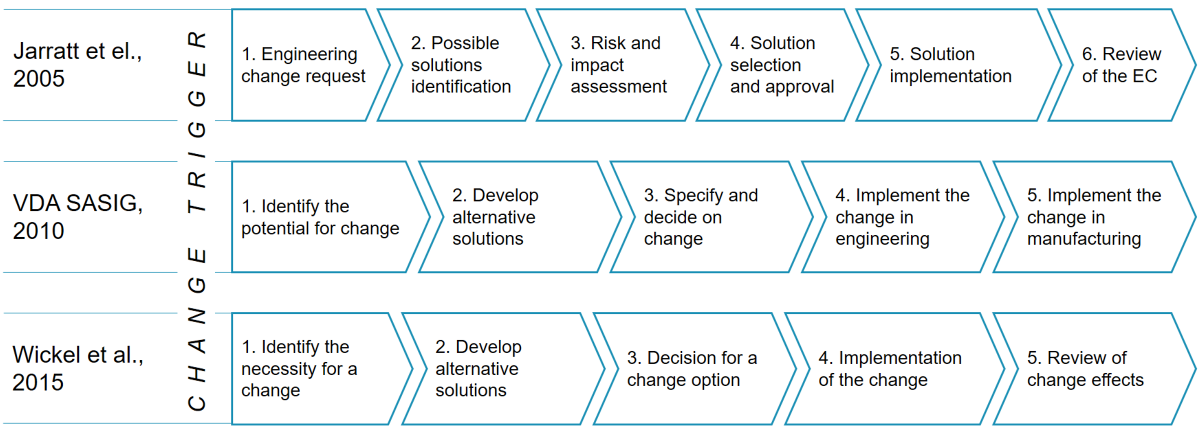

Figure 2.3. Comparison of the phases in generic representations of the ECM reference processes (iteration loops are not shown for figure clarity).

A more recent example of the generic ECM reference process has been derived through the literature review and the workshops with an industry group consisting of the practitioners representing the middle- and large-scale suppliers and original equipment manufacturers (OEMs) (Wickel *et al.*, 2015). Figure 2.3 shows its main stages in the bottom row. The authors have detailed these process stages into eleven process activities involved therein and then asked the experts to allocate their company-specific reference processes atop the literature-based one, which was revised by the experts beforehand. It was found that the firms keep their focus only on the activities directly contributing to closing the target deviation, rarely develop several alternative solutions, and avoid reviewing the implemented changes or process itself. Presumably, those skipped activities – helpful and valuable to project success, as deemed by the research community – consume an unaffordable amount of effort or demand better planning capabilities, and therefore require the aiding analytical tools and methods that would ease their efficient realization.

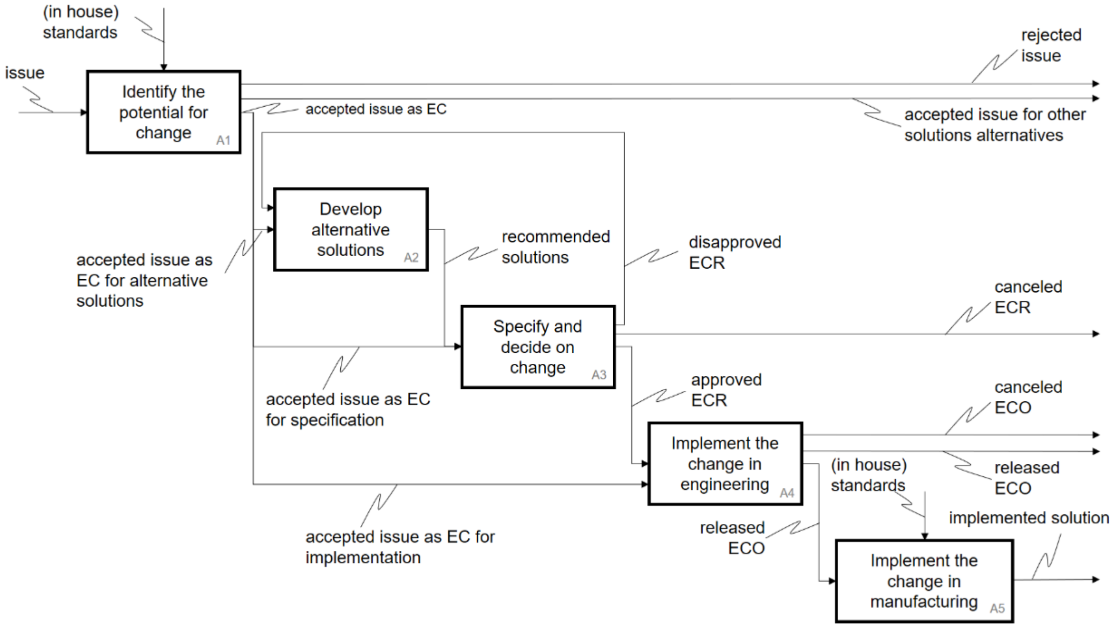

Figure 2.4. IDEF0 representation of the ECM reference process by SASIG, adapted from (VDA 4965, 2010c).

To understand the overall state of ECM-related research, Hamraz, Caldwell, and Clarkson (2013) have conducted one of the latest comprehensive literature reviews and presented an exhaustive framework categorizing the studies relevant to ECM analysis in the mechanical design context. The authors have identified four research clusters associated with ECs pre-change, in-change, and post-change analysis, and with the general studies and surveys on ECM and related topics, i.e., blocks A-D in Figure 2.5. This provides a solid foundation for any further research aiming at either ECM improvement goal stated by Fricke *et al.* (2000): to execute *Less* changes, *Earlier*, *More Effective*, *More Efficient*, and *Better*. One interesting part of this study is devoted to categories interconnection by means of publications citation; with this, authors verify the categorization and draw valuable conclusions on the field development. In relation to CE, this paper argues that since 1992 there is no published research discussing in detail the influence of ECs on manufacturing and post-manufacturing stages (as of 2011). Therefore, this finding spots a same-similar research shortcoming brought in section 2.1.1, i.e., the need to provide better integration of engineering and manufacturing decisions throughout the product creation process. Though there appear efforts elaborating the propagation of ECs to manufacturing systems design, e.g., by Olmez *et al.* (2018), further studies are necessary to consider more granular decisions related to both engineering and manufacturing planning.

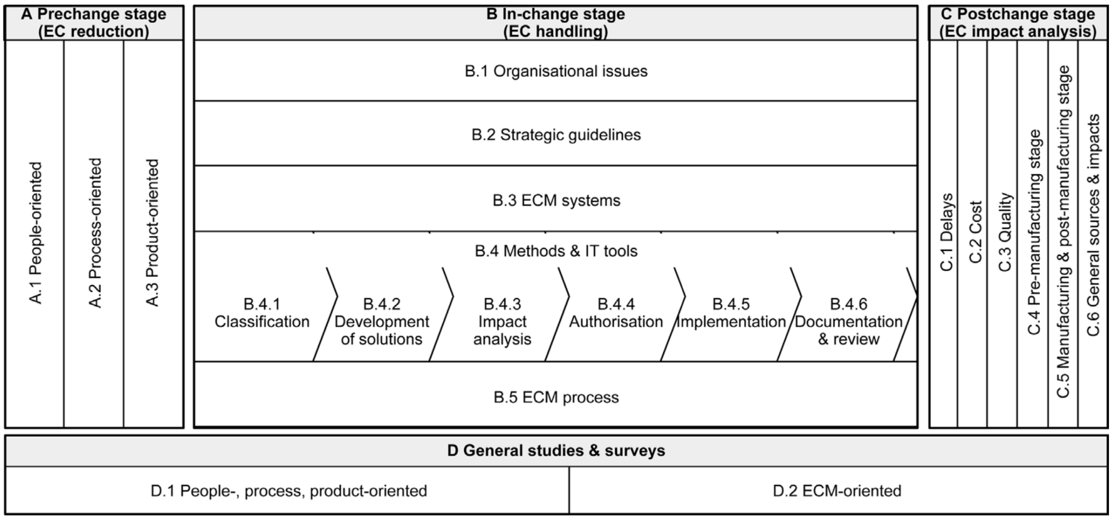

Figure 2.5. Holistic ECM research categorization framework by (Hamraz, Caldwell and Clarkson, 2013).

Considered together, these studies highlight two significant challenges to target in the vein of the first research motivation RM-1:

- Firstly, manufacturing implementation of an engineering change can initiate the iteration loops; manufacturing changes may provoke additional changes in engineering or manufacturing itself, and thus also demand a specific dedicated approach to their management and assessment. Therefore, before looking closer into ECM integration with manufacturing, it is necessary to examine the progress in handling the technical changes in the manufacturing domain.
- Secondly, as the ECM process involves a wide range of associated planning, executing, and analyzing issues (Figure 2.5), and at the same time has a variable architecture that depends on a particular application, its efficient realization requires accurate instrumentation facilitating a context-specific prescription of the necessary set of actions and decisions. Though an extensive amount of effort has been devoted to product-oriented modeling of the change propagation patterns, the process-oriented model-based methods – such as in category A.2 by Hamraz, Caldwell, and Clarkson (2013) in Figure 2.5 or in (Wynn and Clarkson, 2018) – were not addressed in the ECM context so far.

Based on that, the following sections review the associated literature in a corresponding sequence, starting with the manufacturing change management topic.

2.1.3 Manufacturing change management (MCM)

Defining the *manufacturing change* (MC), it is important to understand first the scope of manufacturing. In analogy to a product lifecycle – going through the conceptualization, design, implementation, operation, and maintenance steps – in this work, we would consider the manufacturing domain comprising research in design, operation, and control of manufacturing systems and processes. By manufacturing system, we would imply "*a combination of humans, machinery, and equipment that are bound by a common material and information flow*"; and by the manufacturing process, "*the entirety of interrelated economic, technological, and organizational measures directly connected with the processing/machining of materials, i.e., all functions and activities directly contributing to the making of goods*" (CIRP, 2014).

A first specific definition of a manufacturing change has been recently formulated by Koch, Gritsch, and Reinhart (2016): "*A Manufacturing Change (MC) is an alteration made to the factory or its elements that have been released for or are already in operations. An MC can be of any size or type, it can involve any number of people, and take any length of time*." To incorporate the core ideas from the three definitions given above, this work proposes to derive a formulation explicitly capturing the possibility for manufacturing processes to change by the corresponding informational and material flow alterations. Thus, this work adheres to the following definition of the manufacturing change (MC): *a manufacturing change is an alteration directly related to humans, machinery, equipment, and material and informational flows, straightly involved in the released process of making goods*.

Out of the literature and industry practice review, Koch (2017) has identified the following three domains of MC causes: manufacturing, general occurrences, product development. This categorization appears to be consistent with the list of MC causes synthesized by Macke, Rulhoff, and Stjepandic (2016), and therefore taken as a prime reference.

The manufacturing domain includes such change causes as:

- Factory lifecycle change, e.g., aging of manufacturing resources and related system architecture, modification of internal processes in production, logistics, maintenance;
- Change propagation from preceding MCs;
- Complications in the form of quality-related problems, process interruptions, erroneous operational planning.

MCs due to general occurrences can originate from:

- Laws and regulations, i.e., new or revised governmental laws, guidelines, norms associated with, e.g., environment or workforce safety;
- Introduction of new technologies that alter ongoing manufacturing processes;
- Changes in procurement procedures, supply chain structure;

- Revision of the business strategy, e.g., update of the performance and quality targets;
- Company-wide continuous improvement (Kaizen), e.g., modification of the shop floor operations.

MCs triggered by the product development domain consider:

- An introduction of new products or product variants, change of the production volumes;
- A variety of ECs causing the changes in manufacturing processes or system architecture;
- Failures to meet product requirements in ensuring security, quality, production cost, and functional capabilities.

Going through three case studies, Koch (2017) has found that to handle such MCs, companies can spend around €1,000-1,600 per change only for processing it through an IT-based workflow system, i.e., excluding the expenditures associated with materials costs, engineering efforts, and the like. Undoubtedly, an effective way of governing the MCs thus gets the utmost importance for companies' operational success. Addressing this, researchers have worked on clarifying the *manufacturing change management* (MCM) procedure, which would guide similarly to ECM in the product development domain. Koch, Michels, and Reinhart (2016) have been among the first to define MCM as "*organizing and controlling the process of making alterations in manufacturing, including all measures to avoid or frontload and efficiently plan, select, implement and control manufacturing changes*."

Further, for companies to test or usefully apply an MCM approach, researchers have derived its generic reference process. Reviewing the literature, Koch (2017) has compared early examples of MCM reference processes published between 2004-2015, including the latest available by ProSTEP iViP Digital Manufacturing project group discussed in Macke, Rulhoff, and Stjepandic (2016). It was found that a detailed description of process design and architecture is lacking. Further, he has studied the available reference processes in adjacent research areas – ECM, factory planning, continuous factory planning – and derived the literature-based reference processes for the four fields mentioned above. Additionally, he has empirically defined an industrial reference process based on the case studies. Out of those five generic reference process with different origins, he synthesized a general MCM reference process and then depicted it as a stage-gate model shown in Figure 2.6.

This reference process consists of three phases: proactive, reactive, and retrospective. It includes eight stages total, each ending with a specific gate reflecting the expected deliverables. Though a general view and constituent steps resemble the ECM reference process, the description of each, as given in the thesis of Koch (2017), provides a thorough and complete prescription of the steps to make in a particular manufacturing context. Since none of the previously defined reference processes were sufficient to capture a full MCM scope, this work takes the one developed by Koch (2017) as the major reference.

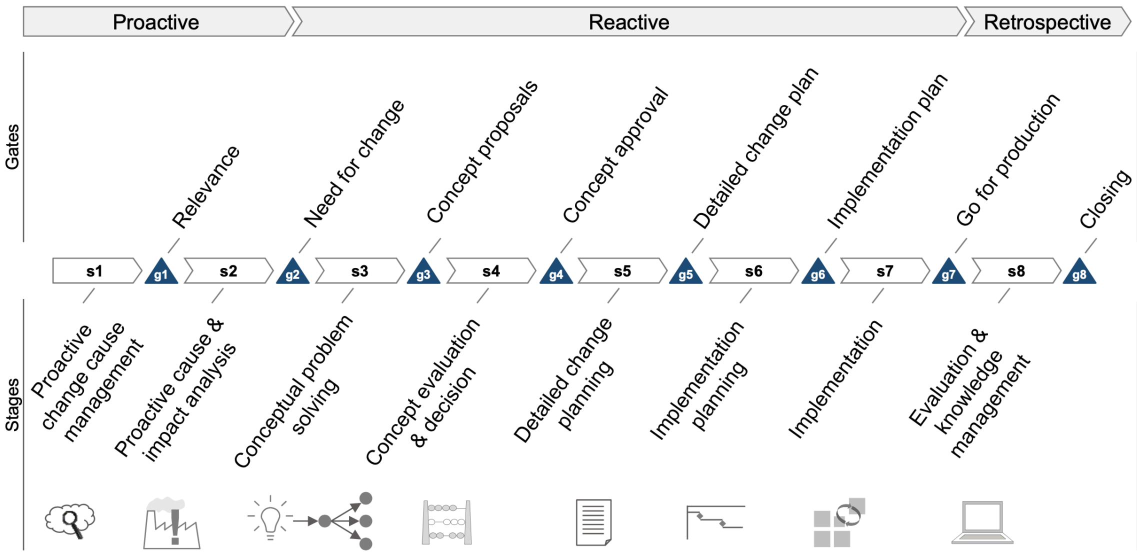

Figure 2.6. Stage-gate model of the general MCM process, retrieved from (Koch, 2017).

Though the current depth of research in MCM is not comparable to that of ECM, this recent work by Koch (2017), along with the work of Plehn (2017), demonstrates a significant contribution to understanding the scope of MC and their possible connections to ECs and other PD activities. It thus provides an ability to further promote a connection of engineering and manufacturing domains by elaborating on the necessary methods and tools for conducting parallel and synchronized multidomain changes.

2.1.4 Towards integrated change management (ICM)

Recognizing the risks of disconnected management of changes in the product engineering and manufacturing domains, associated with the potential for rework triggered by undetected impact from either domain, this work argues that it is necessary to investigate the ways to manage the changes in an integrated manner. An ability to efficiently collaborate, for employees involved in the design, engineering, and manufacturing, when managing ECs or MCs, could improve an overall product creation process by optimizing resources expenditure. In the spirit of concurrent engineering, such *integrated change management* (ICM) should standardize and integrate ECM and MCM steps into one joint procedure and so improve the project's techno-economic performance.

Moreover, as Eversheim and Schulten (1999) show with Figure 2.7, there can be two extremes in setting up a simultaneous engineering practice. In the first case, when the degree of parallelism and integration is insufficient, the PD process experiences more iteration and rework because of poor harmonization of engineering and manufacturing planning activities. In the second case, an exaggerated overlapping of activities leads to the use of ambiguous design information and rework. Logically, there should be an optimal level of parallelism between these two extremes, which would lead to minimal project lead time and, therefore, lower the PD cost.

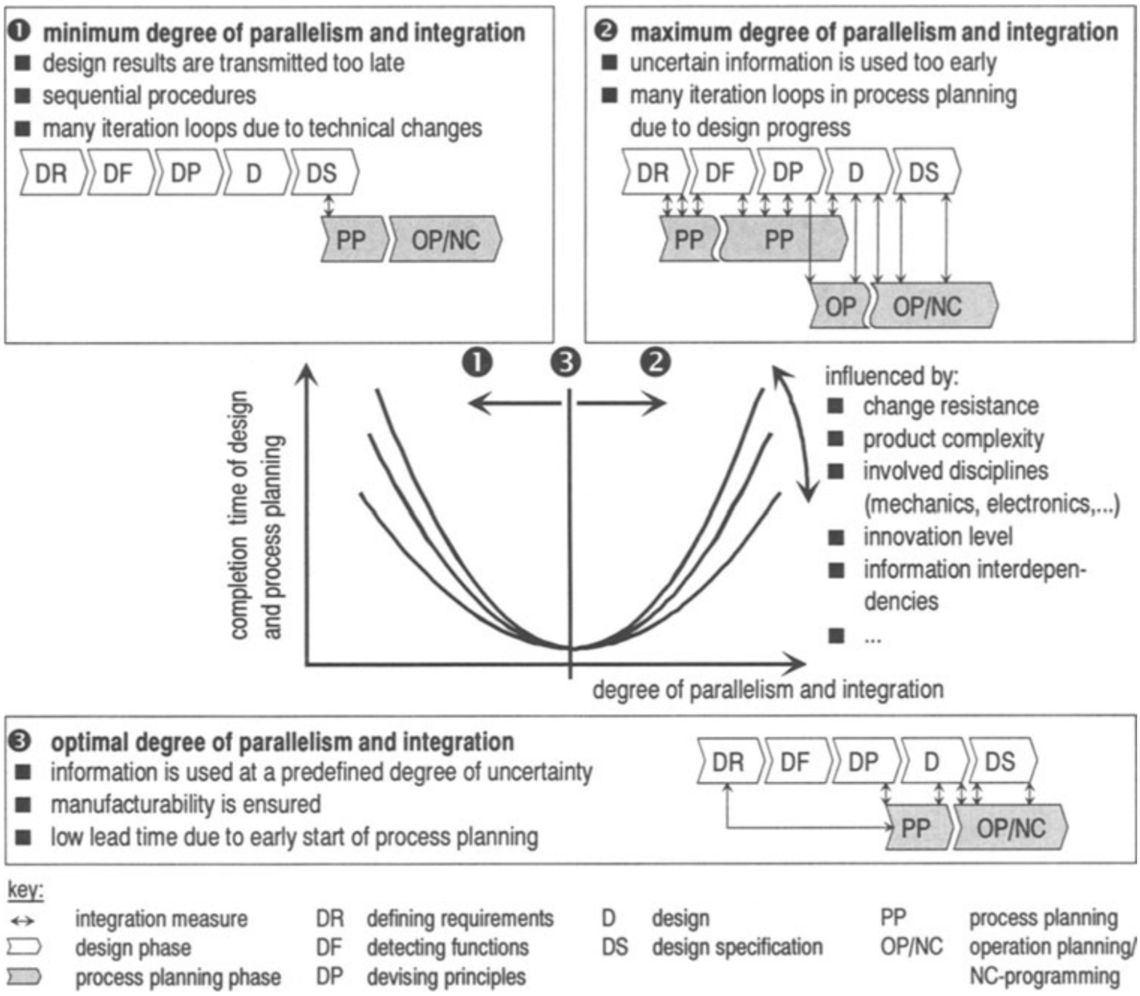

Figure 2.7. On the degrees of parallelism and integration of design and manufacturing planning; retrieved from (Eversheim and Schulten, 1999).

Defining the method for identification of optimal integration, Eversheim and Schulten have developed a goal system measured through eight parameters: use of preliminary information; risk of change; parameter coordination result; starting point of process planning activities; procedure coordination effort; time of change; volume of change; parameter coordination effort. Following it, they evaluated two alternatives of integrating the PD steps and selected a faster option. Though this work underlines a critical concern of selecting an optimal process structure for efficient CE, it seems that it does not provide an instrument or methodology to investigate a full design and manufacturing planning space but only suggests the metrics for alternatives comparison.

Furthermore, since a detailed ICM process would depend on the setting (i.e., industry sector, company policies, product type), its structure and implementation scenario should be tailored specifically to the use case; this variation further expands the process design space. As a result, to obtain a proper ICM process, the firms should have the capability to navigate in process architecture selection in terms of constituent steps, their parametric characterization, sequence, and interrelation, as well as to evaluate the costs of different change scenarios. However, the literature does not cover a quantitative analysis devoted to the ECM or MCM practices. For example, the reviews by Browning and Ramasesh (2007), Hamraz, Caldwell, and Clarkson (2013), or Wynn and Clarkson (2018) discuss the methods for PD process analysis but do not provide specific references to applied studies on ECM or MCM.

Also, since the tasks of handling the ECs and MCs are of the same nature as other PD activities, there is a need to reduce the associated uncertainty of process parameters values that influence the project's resulting time and cost performance. This uncertainty originates from engineering design's creativity and innovation trying to bring something new to each project (Kline, 1985; Browning, Fricke and Negele, 2006). It is complicated by the risk of mismapping or misunderstanding the similarity relationships with previous projects (Eckert and Clarkson, 2010). Uncertainty can also propagate from the lack of knowledge about the system, variation of the physical system or environment, different subjective interpretations of the same phenomena descriptions, or the lack of trust in knowledge (Wynn, Grebici and Clarkson, 2011). Out of the above and in connection with the stated before research motivation RM-1, we formulate **the first research gap (RG-1)**:

> ***RG-1*** *Appreciating the importance of tight collaboration between engineering and manufacturing change management teams, this work emphasizes an immaturity of the integrated change management conception. It lacks the definition and the reference process enabling its practical applicability. Furthermore, there is a lack of explicit methods suitable for quantitative analysis of the integrated change management practice, which can be applied to explore the efficient case-specific process architectures. Given the importance of accurate estimations, such methods should provide the means for the reduction of uncertainty inherent to PD activities planning.*

The identified research gap RG-1 summarizes state-of-the-art enabling the integrated engineering and manufacturing change management and contributes to the basic understanding of the theme necessary to formulate the thesis research question and objectives. Before moving to that, we shift the focus to RM-2 and review the progress and challenges in additive manufacturing industrialization, triggering the transformation of the product creation practice.

2.2 Additive Manufacturing context

Advanced manufacturing technologies use cutting-edge techniques and creative approaches to develop innovative products. Among them, Additive Manufacturing (AM) plays a central role in the evolution of manufacturing (Esmaeilian, Behdad and Wang, 2016) and promises to allow its complete manufacturing freedom through unique capabilities to capture complexity and customization (Conner *et al.*, 2014). Building on the existing AM applications presented in section 1.2, we can argue that the technology has a genuine potential to bring beneficial alterations in the PD and manufacturing processes at their every phase. However, to reach this, the principal barriers of spreading the technology – cost, quality, materials diversity, and size ranges – need to be overcome (Frazier, 2014). Since the current architectures of AM systems are still evolving from rapid prototyping to high volume industrial settings, their cost performance limits the technology use at the latter product lifecycle stages (Baumers and Tuck, 2019). To understand the factors impeding this evolution, our review starts with a concise introduction of AM technologies, then focuses on one of the most promising methods for industrial application, discusses present AM scale-up challenges, and, finally, identifies the research gaps in cost analysis.

2.2.1 The current spectrum of AM technologies

The American Society for Testing and Materials defines AM as *"a process of joining materials to make objects from 3D model data, usually layer upon layer, as opposed to subtractive manufacturing methodologies"* (ASTM, 2013). This distinction allows AM to create ingenious applications via enabling complex geometries such as enclosed internal cavities, porous surface textures, or lattice structures (Quinlan *et al.*, 2017). Similarly to traditional subtractive or formative manufacturing techniques, the additive approach can be realized in various ways, which differ by the necessary feedstock type (e.g., powder, paste, etc.), energy source, nature and sequence of physical processes for feedstock consolidation, and the range of materials. Table 2.1 summarizes the major commercially available AM processes based on the field guide provided by Formnext 2019, the largest worldwide AM exhibition (*AM Field Guide - Formnext - Mesago*, 2019), and the review of the processes developed for advanced ceramics (Lakhdar *et al.*, 2021). The guide's full version is in appendix A1. However, the given list does not claim to be exhaustive as the existing approaches become applicable to other materials, and also novel techniques appear. One recent example is a high-resolution tomographic volumetric AM, in which irradiation solidifies a transparent photopolymer simultaneously from multiple angles with dynamic light patterns (Loterie, Delrot and Moser, 2020). Though this process is currently in its infancy, it already demonstrates another order of productivity: less than 30 seconds for a centimeter-scale part with 80 µm positive and 500 µm negative features. It also better resembles a 3D printing idea since it instantly forms an object's 3D shape as opposed to classic printing of a 2D cross-section per layer.

Table 2.1. The spectrum of commercially available Additive Manufacturing technologies.

Approach	**Method**	**Process names**	**Materials**
Powder Bed Fusion (PBF)	With laser	*Selective Laser Melting* (SLM) or *Laser Powder Bed Fusion* (LPBF)	Metal
Powder Bed Fusion (PBF)	With laser	*Selective Laser Sintering* (SLS) or LPBF	Polymer
Powder Bed Fusion (PBF)	With electron beam	*Electron Beam Melting* (EBM)	Metal
Powder Bed Fusion (PBF)	With agent and energy	*Multi Jet Fusion* (MJF)	Polymer
Direct Energy Deposition (DED)	With laser	*Laser Engineering Net Shape* (LENS)	Metal
Direct Energy Deposition (DED)	With electric arc	*Wire Arc AM* (WAAM)	Metal
Material Extrusion	Green part to be sintered afterward	*Fused Deposition Modeling* (FDM)	Metal, ceramics
Material Extrusion	Material extrusion filament	*Fused Deposition Modeling* (FDM)	Polymer
Material Extrusion	Material extrusion filament	*Continuous Filament Fabrication* (CFF)	Composite
Material Extrusion	Material extrusion granulate	*Arburg Plastic Freeforming* (APF)	Polymer
Material Extrusion	Paste extrusion	*Paste Extrusion Modeling* (PEM)	Any paste material
Binder Jetting	Bonding agent to be sintered afterward	*Binder Jetting* (BJ)	Metal, ceramics, sand, gypsum
Material Jetting	Cured and sintered afterward	*Nano Particle Jetting* (NPJ)	Metal
Material Jetting	Cured with ultraviolet light	*Material Jetting* (MJ)	Polymer
Material Jetting	Microdosing	*Drop on Demand* (DOD)	Wax, ceramics
Photopolymerization	Cured with lased	*Stereo Lithography* (SLA)	Polymer, ceramics
Photopolymerization	Cured with projector	*Direct Light Processing* (DLP)	Polymer, ceramics
Sheet lamination	Lamination	*Selective Deposition Lamination* (SDL) or *Laminated Object Manufacturing* (LOM)	Composite, paper

Trying to analyze an entire AM research field, Li (2019) has studied the publications indexed in the Core Collection of Web of Science (WoS) for author keywords co-occurrence via text mining and identified top ten categories. The three most popular research areas related to AM appeared to be materials science, manufacturing engineering, and mechanical engineering. Since different printing techniques and regimes result in different mechanical properties, dimensional accuracy, surface roughness, or process cost and speed, wide-range studies in those three fields indeed play an essential role in AM maturation. Overall, reviewing AM, it is necessary to recognize the subject's high interdisciplinarity that also varies between the particular applications. Because of this, to facilitate a substantial analysis of AM maturation challenges, from this point, we confine this research to one AM branch – powder bed fusion (PBF) – that is known to have a relatively high technology readiness level (TRL), and which is having a significant growth over the last decade (Schmidt *et al.*, 2017). Furthermore, we restrict our study to metal printing only, as such end-use functional parts are critical to AM expansion across many industries, e.g., aerospace, oil and gas, or automotive (Quinlan, Gee and Shakirov, 2019). Appendix A2 provides a representative list of the metal alloys currently commercially available or in development for a set of AM processes.

2.2.2 Powder bed fusion

To understand the scope and state of a powder bed fusion research field, a part of this review identifies the major PBF research topics by screening the related publications indexed in the Scopus database. It is done via a topic modeling approach based on latent Dirichlet algorithm (LDA), similarly to Xiong *et al.* (2019)[12, 13]. First, using the PBF-specific query[14], we restricted the database to 11,950 journal articles (11,969 originally with 19 duplications found) that have been published between 1987 and 2019. For each article, we included the following information: title, authors, year of publication, abstract, author keywords, citation quantity.

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[12] The topic modeling project has been done within the scope of the "*Ideas to Impact*" course at Skoltech under supervision of Professor Zeljko Tekic.

[13] Credit to Professor Dragan Kukolj, (University of Novi Sad) and Professor Zeljko Tekic (Skoltech) for conducting the LDA analysis on the provided database.

[14] Search query used on October 28, 2019: *(("additive" AND ("manufactur*" OR "mfg*" OR "fab*")) OR (("3D" OR "three-dimens*") AND "print*")) AND ("powder bed fusion" OR ("selective laser" AND ("melting" OR "sintering")) OR "direct metal laser sintering" OR (("3D" OR "three-dimens*") AND "metal printing") OR "high-speed sintering" OR "multi-jet fusion" OR "SLM" OR "DMLS" OR "3DMP" OR "SLS" OR "HSS" OR "MJF") AND (LIMIT-TO (DOCTYPE , "ar")) AND (LIMIT-TO (LANGUAGE , "English"))*

In using LDA, to avoid erroneous topic formulation, we employed the publicly available smart stop lists[15] to exclude the frequently-used words (e.g., “and,” “or,” “that”) from the text-processing analysis. From LDA, we got 93 topics, characterized by the corresponding sets of keywords (1860 total), which then have been reviewed and manually grouped into 30 categories that are further perceived as the prime PBF research areas. In the follow-up processing, we have analyzed the dynamics in annual publications count per group, as shown in Table 2.2 and Table 2.3, as well as compared them in terms of total articles count and citation.

We can see that before 2013-2015, applications-related research was leading the field and, presumably, has shown the limitations of the technology with the need for better materials. From that point, the materials microstructure and mechanical properties topic has grown strikingly over the last five years and now spearheads the research on PBF-based AM. Currently, it has the biggest number of publications, circa 18% of the total count, and includes the most extensive set of topics allocated by the LDA method. It covers the aspects associated with materials heat treatment, microstructure, material strength, and performance-related properties. Also, the number of publications on EBM and SLM, two primary metal technologies in PBF-based printing, has grown considerably since 2012.

Further, we can observe that two emerging AM research fields are getting more significance: post-processing techniques and the supply chain of AM. One possible implication of this tendency is that the industry is starting to take the steps toward technology industrialization and applying it in the serial production context. Both supply chain analysis, as a bird’s-eye view on the process, and post-processing, as an inescapable counterpart of the printing process, are crucial research areas on the way to technology maturation. A commensurate advancement in these fields is necessary to successfully adopt high-volume printing equipment, such as the multi-laser SLM machines with build rates of hundreds of ccm per hour[16]. Finally, whereas we can see that the research community directs almost all its effort on the manufacturing-related challenges, it essentially overlooks the transformation of the product development process brought by the technology. Within 1860 terms chosen by the LDA approach as the most important to PBF, only a few – affiliated with the supply chain and design for AM (DfAM) groups – were appropriate for the description of product lifecycle management.

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[15] Smart stop lists sources:
http://www.ai.mit.edu/projects/jmlr/papers/volume5/lewis04a/a11-smart-stop-list/english.stop
https://raw.githubusercontent.com/ivanvladimir/authorid/4e3bd5b968135380ce839340541892c30d13cf5d/data/stopwords.txt

[16] A current reference for a serial metal LPBF machine can be the NXG XII 600 by the SLM Solutions © with the build chamber of 600x600x600 mm and twelve 1000-watt lasers that are expected to provide a build rate up to 1000 ccm/hour (*SLM NXG XII 600*, 2020).

Table 2.2. The number of publications per year for each PBF research category (part 1).

	Material engineering	Biomedical	Laser engineering	Powder bed fusion analysis	Material and geometry performance	Microstructure and mechanical properties	Powder preparation	Applications	Stresses and strains	Printing parameters optimization	Post-processing	Surface treatment	Simulation	SLS	Thermal issues
1987						1		1							
1989											1				
1990								1							
1991								1			1				
1992															
1993	1							2		1					
1994								1							
1995							1	3						2	
1996								5							
1997								4							
1998	1	1				1		5							
1999		1				1		12							
2000								6			1	1			
2001	2							15		2	1		1	1	
2002			1			3	1	9			2		1		
2003		4	1			1	1	13			2		1	3	
2004		3				2		15		1	1	3	1	3	
2005	3	4	1			1	1	12		3					
2006	2	8				3	3	11	1	3	1			4	
2007	4	10				3	1	17	1	5			1	1	1
2008	2	17		3	1	3	1	13	1	3	2	1	1	2	
2009	4	23		1	1	8		21		5	1		4	3	1
2010	3	19		1	2	10	2	38		6	1		3	4	1
2011	10	30		1	4	16	1	42		6	1	2	2	4	2
2012	7	46	1	1	9	27	4	45	4	6	1	5	4	7	
2013	9	74	2	3	6	33	4	64	10	19	2	6	7	5	1
2014	34	90	1	4	16	61	3	97	10	21	7	10	21	12	3
2015	27	119	5	12	29	105	4	144	16	42	3	19	30	11	2
2016	36	156	12	16	52	207	13	180	28	54	9	38	56	15	7
2017	87	216	19	31	70	342	19	282	70	72	19	40	83	22	11
2018	149	271	34	60	150	535	24	401	101	113	27	86	121	34	18
2019	211	279	30	66	196	748	30	452	141	145	26	128	188	33	21
Total	**592**	**1371**	**107**	**199**	**536**	**2111**	**113**	**1912**	**383**	**507**	**109**	**339**	**525**	**166**	**68**

Table 2.3. The number of publications per year for each PBF research category (part 2).

	316L	EBM	Process investigation	Quality inspection	SLM	DED	MJ and BJ	WAAM	Review articles	DfAM	SLA	Supply chain	FDM	Sustainability	Optical issues
1987															
1989															
1990											1				
1991															
1992			1												1
1993															
1994									1						
1995															
1996			1						1						
1997				1					1						
1998			1						3						
1999								1	2			1			
2000			2				2		1		1		1		
2001					1		1		2			1			
2002			1		1		1	1	2						
2003			2			1	1		1						
2004			3		1				1						
2005			3						1						2
2006			2	1	1		1		3		1				2
2007			4			1						1		1	2
2008			6	1	1		1	1				1			
2009			8	1	3	1	1		6	1	2	1			
2010		2	11	2	3	1			4			2		1	2
2011		4	7	5	2	1			3	2	2				4
2012		3	13	3	4	2	2	1	5	3	2	4	1	1	3
2013	1	2	19	5	11	1	2	2	5	5	4	3	2	3	8
2014	5	7	31	12	18	2	5	2	22	4	3	5	7	6	6
2015	3	14	61	17	24	5	7	7	32	10	3	8	8	3	18
2016	8	18	72	28	37	8	12	6	26	16	1	12	11	6	18
2017	16	31	129	41	24	25	16	15	23	40	7	12	21	18	14
2018	37	32	190	94	41	26	24	26	41	60	8	18	36	18	27
2019	47	56	212	98	50	30	29	38	50	72	18	33	31	12	29
Total	**117**	**169**	**779**	**309**	**222**	**104**	**105**	**100**	**236**	**213**	**53**	**102**	**118**	**69**	**136**

Summarizing the above, we can note that research mainly focuses on mechanical properties and microstructures analysis, the study of AM applications (especially biomedical), and printing processes investigation, as shown with the blue region in Figure 2.8. The total number of citations per group shown with the red region in Figure 2.8 mostly correlates with the articles count, except for the review articles that historically have higher citation values.

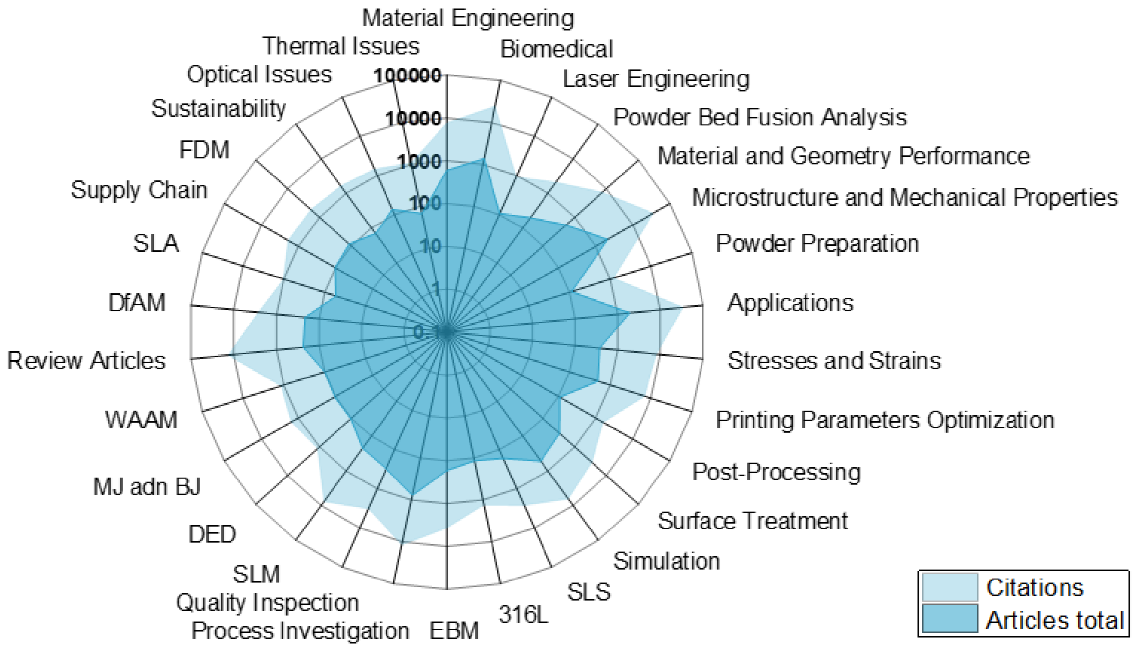

Figure 2.8. The map of major research topics in PBF AM: blue region indicates a distribution based on the total number of articles in a group; red region indicates the total number of citations in a group.

When adjusting the citation numbers to articles count and excluding the reviews from comparison, we can see that the most cited works, on average, are related to SLM, i.e., LPBF of metals, followed by sustainability, EBM, and material properties investigation, as shown in Figure 2.9. These findings suggest that the LPBF approach has a high research impact and seems to be coherent with the notions on the topic's growing prominence stated by Schmidt *et al.* (2017). Therefore, in selecting a specific PBF process for in-depth investigation, we can additionally confine the research scope to LPBF.

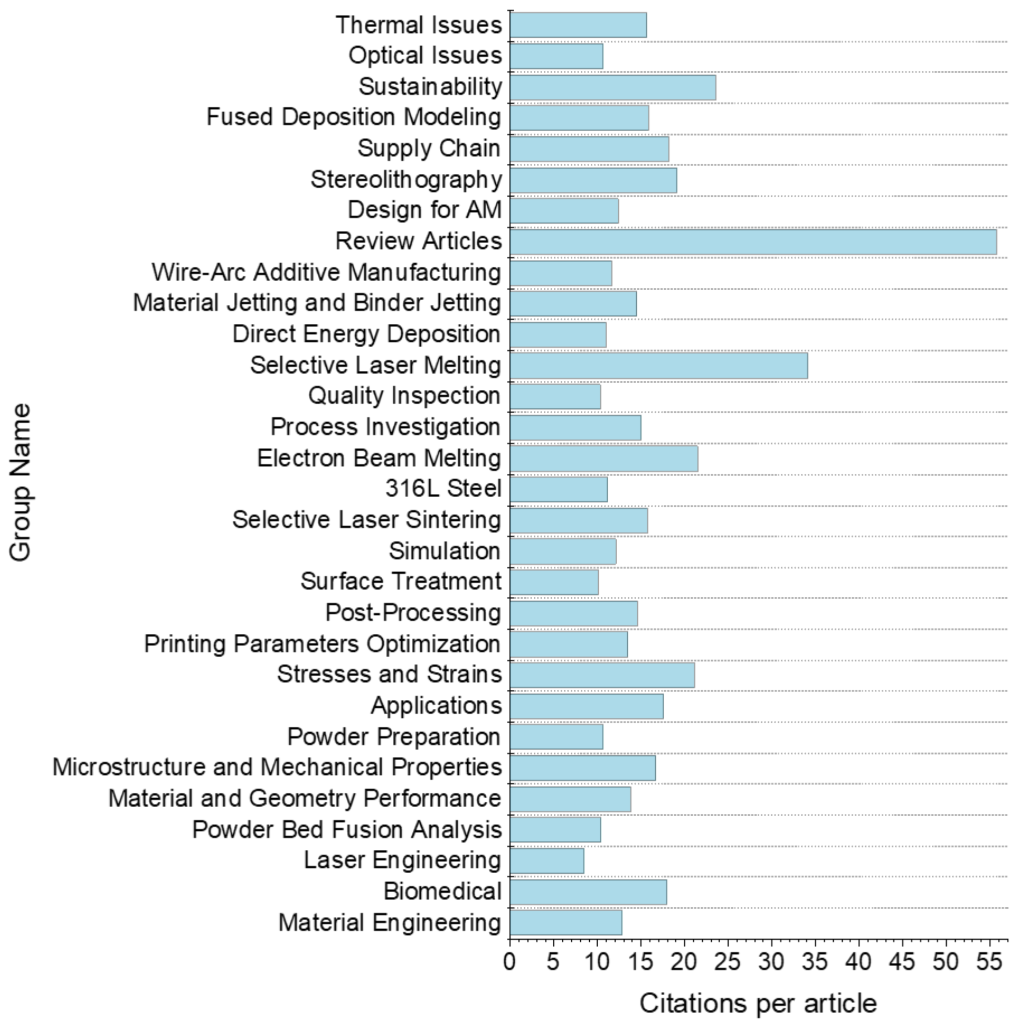

Figure 2.9. An average number of citations per article for each group.

2.2.3 Laser powder bed fusion (LPBF)

According to International Organization for Standardization, LBPF is defined as a "*process used to produce objects from powdered materials using one or more lasers to selectively fuse or melt the particles at the surface, layer upon layer, in an enclosed chamber*" (*ISO/ASTM 52900:2015(en), Additive manufacturing - General principles - Terminology*, 2015). That is, by transmitting energy to locally melt the powder (in the region of circa ø100µm), LPBF allows to produce the parts layer by layer in the widest range of metal materials (see appendix A2). The principal scheme of the process, given in Figure 2.10a, shows the main elements of the system repeating four consequent steps: (1) the scrapper spreads the layer of powder fed by the feed container on to the build plate; (2) the excessive powder goes to the overflow container; (3) the laser goes through the system of lens and mirrors and melts a necessary pattern of the layer; (4) the build platform steps down for the height equal to layer thickness. The resulting quality of parts printed via LPBF, such as those in Figure 2.10b, would differ in terms of microstructural features, e.g., grain size, texture, roughness, and in such mechanical properties as strength, hardness, or residual stress (Gu *et al.*, 2012). To achieve the desired outcome, it is necessary to fine-tune the powder characteristics, i.e., particle shape, size, distribution, powder chemical composition, packing density, and flowability, as well as the processing parameters, i.e., laser type, spot size, power, scanning speed, hatch spacing, and layer thickness. Moreover, in seeking an optimal setting, one would need to balance the quality-productivity tradeoff, as the same parameters impact the output rate of the process (Gusarov *et al.*, 2018). Though these considerations are fundamental to the quality- and cost-performance of the LPBF process, when studied from the industrialization potential perspective, it should not be considered separately but within the workflow, including all necessary preceding and succeeding work in a shop floor context.

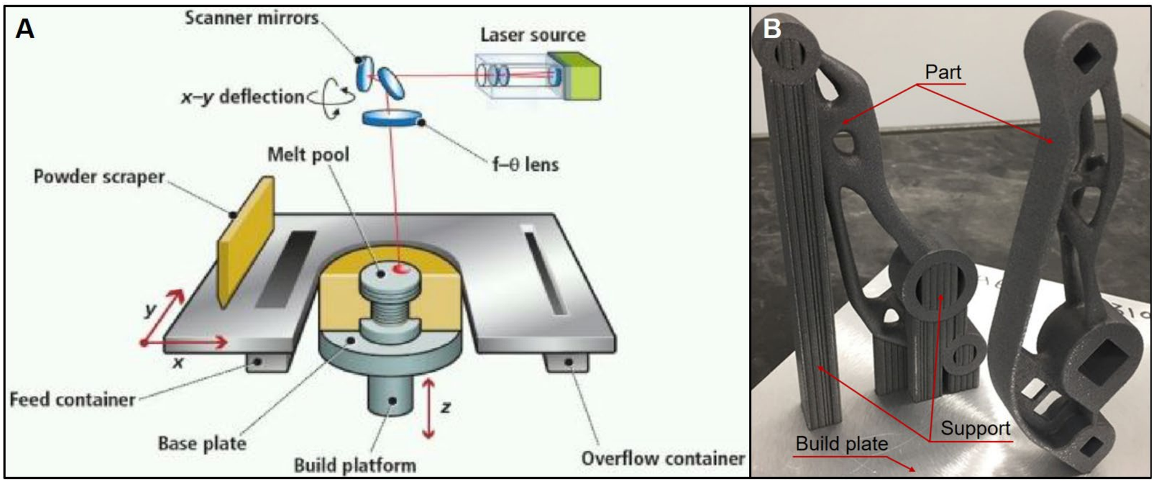

Figure 2.10. (a) LPBF principal scheme of operation (Schmidt *et al.*, 2017). (b) Two suspension bell-cranks produced via LPBF. Left: geometry-optimized bell-crank without manufacturing constraints applied. Right: geometry-optimized bell-crank with manufacturing constraints applied[17].

Like other AM processes, LPBF-based manufacturing can be segregated into the pre-processing, processing, and post-processing stages. Pre-processing stage, which is also called *build preparation*, covers all manipulations with the component's digital representation – usually by means of computer-aided design (CAD) and computer-aided engineering (CAE) tools – to define its geometry for the printing process. At this stage, an engineer adapts the build's design for additive manufacturing (DfAM) by balancing between the design goals and manufacturing constraints. It incorporates, among others, the tasks of parts' orientation definition, topology optimization of the structures for reduced material and energy use, and part design modification for better manufacturability.

Zhang *et al.* (2017) argue that an optimal build configuration must consider both how to generate a final set of orientation alternatives and then how to select the best one. This formulates a two-step problem that can become a multi-objective NP-hard problem if it would address several optimization criteria.

[17] Original picture source:
https://www.linkedin.com/pulse/topological-optimisation-really-optimal-marc-saunders

Possible objectives of build re-orientation are minimization of surface roughness, total build time, or supports volume for manufacturability improvement due to lesser post-processing effort.

Furthermore, part design manufacturability itself depends on many factors. One of them is a critical surface angle defining the volume of support geometry and, e.g., the hole shape: Figure 2.10b illustrates the transition from cylindrical holes on the left part to square holes on the right part. Hence, it affects the design of the sacrificial support shown in Figure 2.10b left and self-supporting geometries shown in Figure 2.10b right (Thompson *et al.*, 2016). Support structures can be thermal or mechanical, preventing the build from warping due to thermal stresses or the parts from shifting during powder spreading by the blade (scrapper) (Elliott and Love, 2016). The build preparation stage also includes the setup of the processing parameters discussed above.

Vaneker *et al.* (2020) complement the discussion of various DfAM challenges, including lightweight design, optimization of the surface structure and internal part topology, design of functional materials, and assembly and part integration. To encourage consideration of all relevant aspects, the authors propose the framework incorporating the objective-specific methods and tools, relying on the ISO/ASTM 52910:2018 standard for using AM in product design. A further extension of considerations would involve a multi-scale analysis: on the example of the metal LPBF process, Gu *et al.* (2021) present a material-process-structure-performance concept addressing the AM-related issues from the nano- to macro-scale. Ultimately, this all determines a complete set of digital instructions for the printer, which are usually converted to a Standard Tessellation Language (STL) format file that is then uploaded to the AM machine (Salmi *et al.*, 2018).

The processing stage, i.e., *printing*, includes machine setup, printing, and machine recovery. Printer preparation involves installing the build plate, powder hoppers (containers) refilling shown in Figure 2.11a, powder compressing in a feed hopper for homogeneous spreading shown in Figure 2.11b, and build chamber vacuuming and inerting once the print is initiated. Depending on the lifespan, inert gas tanks, filters, lenses, blade resin gaskets, and other consumable units might need replacement before print initiation, as shown in Figure 2.11c-d. The LPBF process in Figure 2.12a executes four steps described above in Figure 2.10a, with possible breaks for powder hoppers refill in longer builds (Elliott and Love, 2016). As Figure 2.12b shows, the machine outputs a statistics report that details the total job duration, gas consumed, filter's life status, and other process-specific information when the printing is completed. The recovery starts with build chamber venting and cooling down. The operator cleans the printing area, e.g., by brushing out an excessive powder to the overflow hopper for further recycling (Figure 2.13a), vacuuming the chamber (Figure 2.13b), removing the build plate (Figure 2.13c), cleaning the lens from the powder (Figure 2.13d), and wiping the hopper sealings with alcohol (Figure 2.13e).

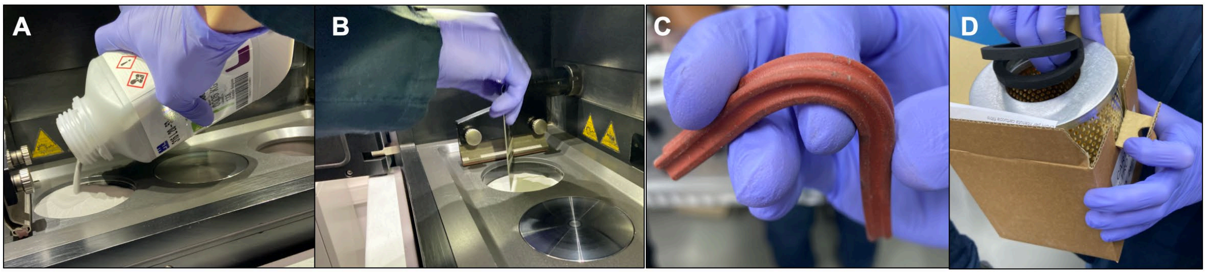

Figure 2.11. Exemplary machine setup operations[18]: (a) manual filling of the powder feed hopper; (b) manual compressing of the powder; (c) cracking defect on the blade resin gasket; (d) replaceable filter.

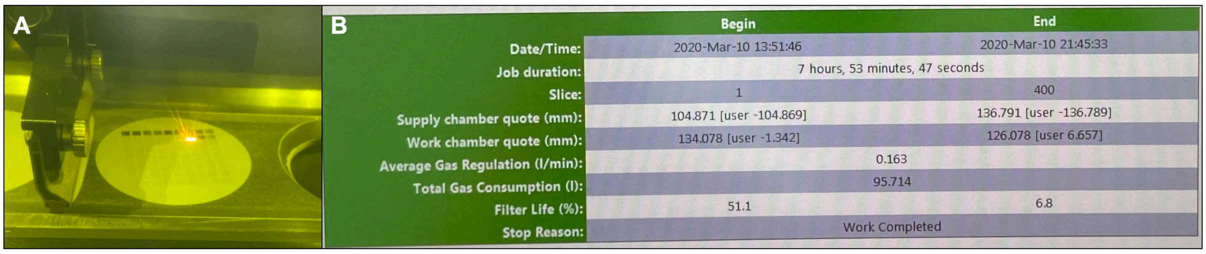

Figure 2.12. The LPBF process: (a) Photo of laser melting the powder; (b) fragment of the print statistics report[19].

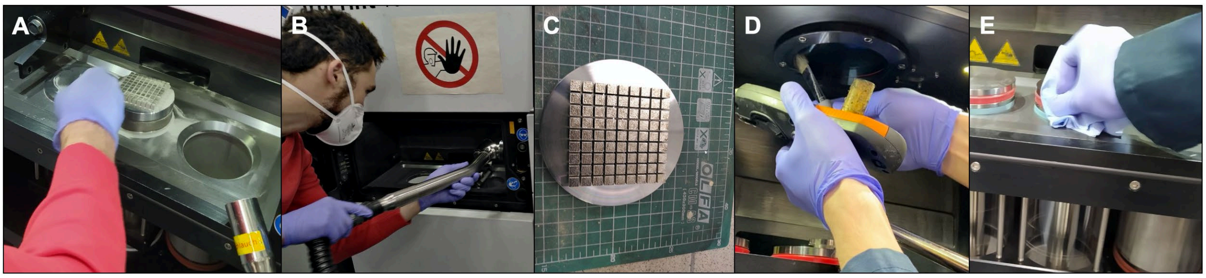

Figure 2.13. Exemplary machine recovery operations[20]: (a) brushing the excessive powder to the overflow hopper (note the vacuum cleaner head sucking the particles from the air, bottom right corner); (b) vacuuming the build chamber; (c) deinstalled build plate; (d) cleaning the lens; (e) wiping the hopper sealings with alcohol.

The *post-processing* stage consists of various activities performed after printing to finish the parts and ensure their technical requirements. Depowdering of the build is necessary to remove the excessive powder encapsulated in the cavities; special equipment can be used for massive parts and process automation, such as in Figure 2.14a. To eliminate the residual stresses typical for the LPBF process, a stress-relieving heat treatment cycle is usually required for each component (which may be batched into a single furnace cycle). For further individual processing, the parts are separated from the build plate; this can be done, e.g., using the bandsaw as in Figure 2.14b-c or more accurate wire electrical discharge machining (EDM). Meisel *et al.* (2017) demonstrate that it can be the most difficult step of the workflow

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[18] Photos has been taken during the Skoltech's "Fundamentals of Additive Technologies" course of Spring 2020 (machine used – "TruPrint 1000" by Trumpf).

[19] Photos has been taken during the Skoltech's "Fundamentals of Additive Technologies" course of Spring 2020.

[20] Ibid.

if non-optimal manufacturing parameters are used during the heat treatment or sawing processes. For example, insufficient inerting during solution annealing can lead to surface oxidation and low cutting rate can dull a band saw blade. Moreover, the support geometries, which are comprised of the same material as the main part, require manually intensive removal after printing, as shown in Figure 2.14d. However, pursuing process automation, a plasma electrolytic polishing process[21] can be considered (Bagehorn *et al.*, 2017). Then, other finishing steps may be taken to improve the part's surface properties, e.g., by sanding, blasting, tumbling, or its mechanical and metallurgical properties, e.g., by using a high-cost hot-isostatic pressing machine shown in Figure 2.14e (Bagehorn, Wehr and Maier, 2017).

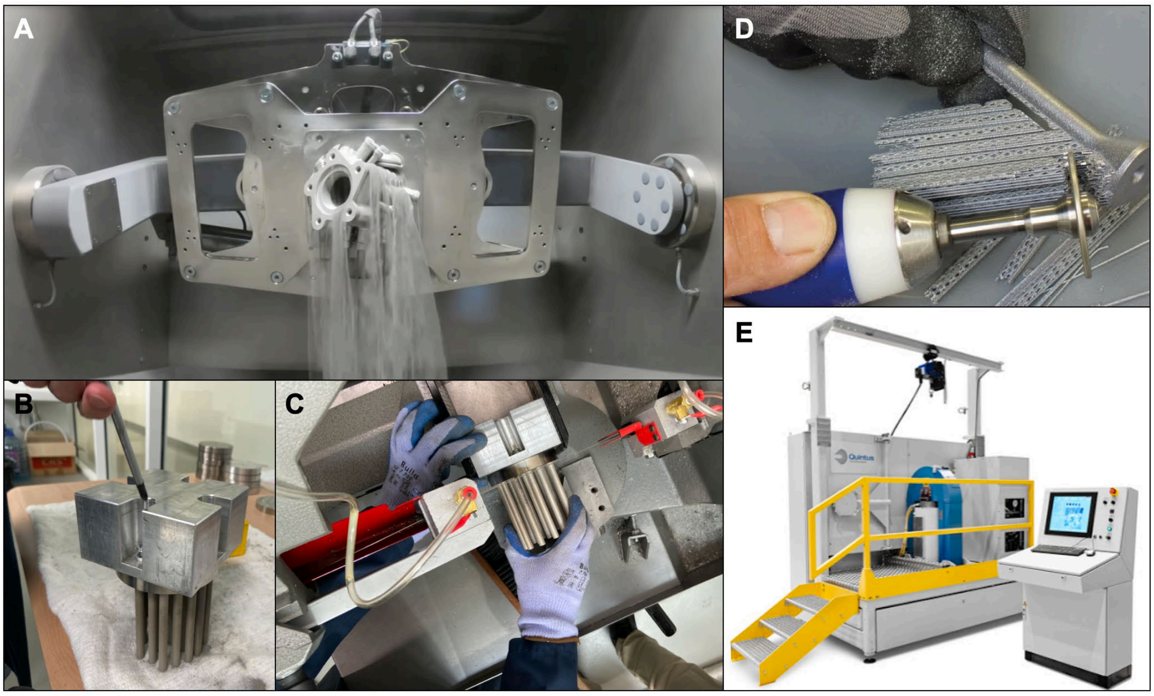

Figure 2.14. Post-processing of the printed components: (a) Automated depowdering machining[22]; (b) build plate installation on the bandsaw tooling[23]; (c) build plate separation using a bandsaw (top view)[24]; (d) metal supports manual removal[25]; hot-isostatic pressing (HIP) machine (e)[26].

Finally, functional end-use components require a thorough quality control (QC) procedure along the LPBF workflow. The common inspection methods include visual inspection, optical metrology, dye

[21] References to commercially available solutions: https://www.rena.com/en/innovation/hirtisation/ or https://www.youtube.com/watch?v=CyS5x2ItT8o&t.

[22] The picture has been retrieved from https://www.solukon.de/en/metall/

[23] Photos has been taken during the Skoltech's "Fundamentals of Additive Technologies" course of Spring 2020.

[24] Ibid.

[25] Figure source: https://www.swissplasticsplatform.com/en/showcase/en/equipment-for-3d-print-finishing-np-2.

[26] Figure source: https://www.metal-am.com/quintus-supply-hot-isostatic-press-sintavias-metal-additive-manufacturing-facility-florida/.

penetration testing, and computed tomography (Garzaniti, Golkar and Maggiore, 2019). In AM, the inspection complexity is associated with intrinsic to printed parts complex freeform shapes, nontrivial texture geometries, multiple occlusions, difficult-to-access features, and wide material range with different optical and surface properties. Because of the high after-print surface roughness, the precise tactile and optical coordinate measuring machines (CMMs) are typically not used until the post-processing is done. Alternatively, an X-ray computed tomography (XCT) scanning – a time-consuming process for the object's holistic volumetric modeling – can be applied to overcome the limitations with small features and complex surface texture. XCT is usually used for inspecting the geometry of internal features and the material's quality to detect an undesired porosity. Furthermore, since capturing the porosity defect after printing means wasting resources on useless work after the defect's appearance, researchers are developing in-process monitoring systems to locate them early in the process. A term for one such technique that is getting increasingly popular is "optical tomography"; it combines the layers' images into a single 3D model to facilitate the search of internal defects (Leach *et al.*, 2019).

Taken in total, we see a long sequence of steps in the LPBF-based manufacturing workflow that spans from build preparation to parts final quality control. Given that, realizing the "just press print" vision mentioned in (*The Economist*, 2011) can take a considerable time for overcoming, at least, the stated above issues and automating the process. Furthermore, the motivation for technology maturation has to come from the identification of its cost-efficient applications. For this, the navigating tools are needed to provide an accurate evaluation of the techno-economic performance of an AM-enabled manufacturing system. Especially, the cost and duration of build preparation (which strongly depends on the connection between engineering and manufacturing activities), post-processing, and quality control tasks are critical considerations of any assessment approach for the AM process.

2.2.4 Analysis of the LPBF-based manufacturing workflow through cost modeling

The accurate assessment of any system aims to predict its behavior and identify the most appropriate operation scenario. Studying multidisciplinary subjects, engineers use various models to represent reality, building on a set of assumptions that restrict the system's natural complexity and eventually entail a modeling error (Hazelrigg, 1999). In relation to the analysis of beneficial AM applications, researchers have developed a variety of cost modeling approaches to understand the influence of numerous process factors and provide guidance in creating efficient AM-enabled production systems. In early studies on rapid manufacturing, Hopkinson and Dickens (2003) calculate the costs of producing one part type via various AM methods, breakdown them into categories – machine, labor, and material – and compare with injection molding costs to define reasonable production volumes for AM. However, as pointed in a follow-up work by Ruffo, Tuck, and Hague (2006), the authors have overlooked machine costs amortization that deflects the cost curve at low production volumes. Ruffo, Tuck, and Hague (2006) also found a saw tooth shape of the cost curve reflecting an influence of the bed-space filling fraction by acknowledging operation time as a cost driver at machine setup, processing, and recovery steps. This particular consideration was an essential contribution to AM cost modeling accuracy. Later, Baumers *et al.* (2015) discuss an impediment to AM scale-up being low productivity of the technology, which is incomparably less than that achieved by conventional manufacturing methods (well over 100 kg/h). Authors argue that overcoming this limitation is more important than reducing the printing systems' costs since "*the overheads resulting from running a large number of unproductive systems may result in prohibitive total expenditure.*"

Though these models provide an in-depth study of printing cost factors and limitations, they seem to neglect an influential role of build preparation and post-processing stages and also pull out AM cost and productivity assessment from the shop floor context. As a result, these models seem insufficient to describe the series manufacturing operations with a realistic granularity and study the system performance indicators, e.g., a specific volumetric cost index ($/ccm) mentioned by Baumers and Tuck (2019). Particularly, they omit production planning issues such as selecting a batching strategy, configuring a system (e.g., choosing the number of machines, number of workers, shift mode, shop floor layout), defining the machines assignment sequence, determining a quality control policy, or accounting for the costs of producing defects. Thus, they appear to be inappropriate for case-specific evaluations of AM costs and therefore are not suitable for quantitative analysis of implications brought by engineering or manufacturing changes at a full workflow scope, which is necessary to address the research gap RG-1. Furthermore, in addition to cost analysis, precise evaluations of productivity and lead time are critical in AM-enabled system design and assessment of associated ECs or MCs. Hence, a robust AM modeling approach should provide the capabilities for duration estimation of the constituent steps and the process overall. Certainly, such analytics would also be a critical component for designing efficient supply chains, such as with decentralized manufacturing that is vital for AM maturation (Baumers *et al.*, 2015).

Addressing the above challenge, other works have developed the cost models filling some parts of stated limitations. For example, Garzaniti, Golkar, and Maggiore (2019) have captured a complete AM workflow and used an exhaustive list of recurrent and non-recurrent costs associated with the LPBF- and EBM-based processes. Yet, aiming to build a tool for AM suitability analysis for a given part design, the authors did not study the influence of production planning decisions in detail. Mounsey, Hon, and Sutcliffe (2016), oppositely, have used simulation to accurately investigate some planning issues (staffing levels, shift patterns, build duration) but omitted pre-processing, post-processing, and quality control procedures in LPBF. Stittgen and Schleifenbaum (2020a, 2020b) studied key performance indicators (KPIs) of the LPBF station, such as its utilization, throughput rate, and work in progress (WIP), but considered an incomplete workflow and did not provide cost-based evaluations.

Therefore, the presented so far analytical tools for AM assessment either do not cover a whole process workflow, or do not investigate production planning questions, or do not examine the time-cost tradeoffs. Accordingly, they can only be partially applied in research on technology scale-up and its further impact on engineering and manufacturing practices. From this, we identify **the second research gap (RG-2)**:

> ***RG-2*** *Evaluating the potential of AM technologies and LPBF, in particular, to reshape the product lifecycle by, foremost, enabling the production of functional end-use components with unavailable before complexity and customization, this work recognizes a lack of analytical model-based methods enabling quantitative assessment of Additive Manufacturing impact and providing a detailed consideration of production planning issues.*

2.3 The current state of Integrated Change Management analysis in the AM context

The goal of ICM is to bridge ECM and MCM, and thus increase their effectiveness, i.e., reduce project costs and lead times. Studying ICM in the AM context even more stresses the need for integration in product and process design due to technology's direct digital connection between engineering and manufacturing (Salmi *et al.*, 2018). Therefore, the combination of ICM and AM forms a very specific research niche, which presumably promises to play an important role in the successful development of either domain. Since the evidence of deliberate analysis within this niche is currently missing, this work emphasizes a lack of determined, analytical frameworks for assessing managerial decisions on ECs or MCs in an AM-enabled environment. Furthermore, though the general idea of integrated analysis across engineering and manufacturing domains is not new, it is still not well developed for the system's quantitative techno-economic evaluation.

Specifying the twelve hypotheses on product-process integration benefits, Swink (1999) notes that the possible tradeoffs in PD and manufacturability management need exploration. Freedman (1999) promotes an integrated umbrella software package, which resembles the core of modern PLM systems, to connect the product, process, resources (PPR), and knowledge throughout the PD stages. Building on an analogy of drawing practice transformation triggered by the introduction of Computer-Aided Design (CAD), the author argues that an integrated digital environment would facilitate manufacturability improvement and reduce expenditures due to more efficient configuration management relying on simulation-based validation. Freedman suggests that simulation modeling – a widespread instrument in manufacturing and business analytics nowadays (Jahangirian *et al.*, 2010) – promises to overcome the challenges associated with representing the product creation system complexity. It provides deep granularity in system description, building on a thorough and organized digital representation, and captures system's time dynamic behavior (Evans and Haddock, 1992).

Simulation's potential can be further strengthened through combination with the visual representation means replicating a system's physical embodiment, as discussed in (Tolio *et al.*, 2013).

Vandevelde, Dierdonck, and Clarysse (2002) have developed a regression model based on the interviews' data to study the managerial integration factors for smooth production ramp-up. The authors point out that formalization of the management mechanisms and empathy from design to manufacturing – i.e., when designers care about product manufacturability and have an aspiration to account for inter-functional differences – can help to overcome the major barriers of design-manufacturing integration, such as personality and cultural differences.

Park and Simpson (2003, 2005) argue the need for production cost estimation frameworks providing consistent and accurate evaluations at the early stages of product family design. Particularly, the authors propose to evaluate the decisions on commonality within the product family, i.e., the extent of sharing the components across the products, by using the activity-based costing (ABC) method and mapping it on the product family structure. With this approach, they study the production costs in screwdrivers manufacturing and investigate the effects of commonality and variation in production volume. In conclusion, Park and Simpson suggest that further work is necessary for careful consideration of higher-level activities; this, presumably, corresponds to the batch, product-sustaining, and facility-sustaining activities discussed by Cooper and Kaplan (1991). In turn, the analysis of the higher-level activities would impose additional requirements on framework analytical capabilities related to consideration of the production planning decisions.

Michalek *et al.* (2006) approach integration of engineering and manufacturing planning via the analytical target cascading (ATC) modeling method. In their work, the authors have connected the product design and marketing decisions with two manufacturing planning decisions: selection of machine types and their quantity (Figure 2.15). Though the chosen modeling approach does provide modularity in problem definition, i.e., what kind of considerations to make in the analysis, it might be inefficient to cover a wider spectrum of manufacturing system design and production planning decisions comparing to, e.g., simulation-based methods (Evans and Haddock, 1992; Labitzke, Spengler and Volling, 2009). Defining multitude details concurrently in several domains demands bulky mathematical formulations, which need to be defined around an efficient model architecture. Manufacturing system modeling solely needs great detail in consideration of the shop floor operations, such as those described in sections 2.2.3-2.2.4. This imposes vast effort requirements on data and its dependencies' coordination that seems to be irrational executing through analytical expressions.

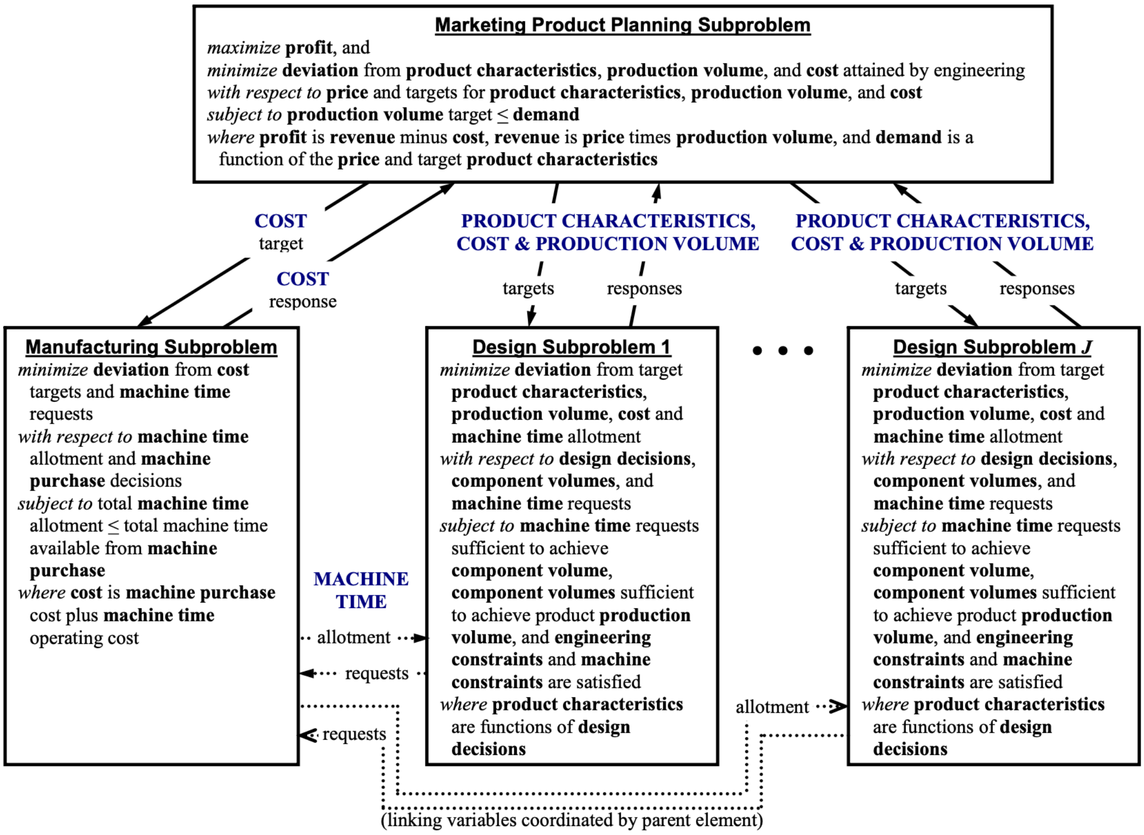

Figure 2.15. Coordinating marketing, engineering design, and manufacturing decisions using the analytical target cascading technique; retrieved from (Michalek, 2005).

Later, Curran *et al.* (2007) present the work that realizes the vision discussed by Freedman. The authors demonstrate a simulation-based environment for aircraft fuselage panel design and assembly, which connects the data across the PPR domains and considers the performance and economic aspects. In a similar work, Lin, Lee, and Bohez (2012) introduce an integrated framework for helicopter blade conceptual design and assembly analysis. It includes an activity-based costing (ABC) module for parts cost estimation and an analytical queueing model for production performance evaluation. The authors conclude that in future work, various production planning factors shall complement the product design parameters considered in the developed solution.

We can see that the literature discusses the competing objectives in product and its manufacturing process design, improvement of production techno-economic performance, as well as the partial integration of these aspects into comprehensive analytical systems. However, neither of the presented works incorporates these all considerations into one study. Nor do they examine the ways to manage such an integrated analysis. The literature explores the linkages between the product and manufacturing process design but does not study the influence of the planning decisions involved in architecting the product creation system. Conducting efficient integrated changes requires well-organized inter-domain coordination yielding a reliable and robust process that builds on the structures of PD and production systems. Matching the practices employed for PD and manufacturing is critical as excellence in practice chosen for operations in one domain can be eroded by the inappropriateness and weakness of a chosen practice in another (Koufteros *et al.*, 2014).

Therefore, this work aims to supplement the discussed above research objectives on integrating engineering and manufacturing studies with an investigation of the process planning decisions improving the product creation system's time- and cost-based KPIs. By this, our work aims to advance the field of product development towards complete integration of the involved internal (related to the product, process, and organization domains) and external (related to customers, suppliers, etc.) factors (Hassannezhad and Clarkson, 2017).

Concluding on the above, we can re-emphasize and expand the challenge highlighted by Ford and Sterman (2003): the theory related to integrated management of the engineering and manufacturing processes has addressed the precedence relationships among the activities and the team behavioral issues in designing the product creation system but not the inter-domain linkages. Though the inter-domain connections have received more attention at the level of product and its manufacturing process design, the model-based analysis on planning the engineering and production activities remains unaddressed to a large extent. Thus, this work identifies **the third research gap (RG-3)** that is critical to address by providing an adequate analytical framework:

RG-3 *There is a lack of the modeling frameworks that could capture the engineering and manufacturing domains in integration to conduct quantitative techno-economic analysis of the managerial decisions associated with planning the product creation process, especially in the context of AM-enabled production.*

Taken in total, it is seen that on the way to the digital manufacturing era, we meet a critical challenge to enable cost-efficient integrated changes in engineering and production in the AM context. As researchers have developed separate reference processes for handling engineering and manufacturing changes, now it seems necessary to connect the domains relying on a combined quantitative assessment of the associated engineering and manufacturing planning decisions. Moreover, new advanced technologies, such as AM, impact the common product development and production planning practices and, undeniably, affect engineering and manufacturing change management processes. Summarizing and building on discussed so far specifics of ECM, MCM, ICM, and AM, we can argue that the need to make numerical evaluations of the relevant cost- and time-based metrics imposes certain requirements on the missing framework. As such, it shall be able to:

- Represent the case-specific ICM reference process, i.e., depending on a company and component of study, by defining the constituent activities, their interconnections, and quantitatively characterizing iteration and rework inherent to the product development process.

- Enable the sensitivity analysis for the ICM process's major variables via calculating the associated cost- and time-based metrics.
- Model a case-specific AM-enabled manufacturing system and process, capturing the pre-processing, processing, post-processing, and quality control activities.
- Enable the study of the related production planning decisions.
- Analyze the techno-economic performance of the manufacturing system in terms of the selected set of indicators.
- Provide an integrated quantitative assessment of the product development and manufacturing indicators within one analytical system.

Based on this, we can now formulate the research question and objectives that need to be addressed to fill the gaps.

2.4 Problem Statement

As stated in section 1.2, a global research objective of this work is to "*develop an approach for quantitative assessment of AM influence on the product creation process that will support the improvement of engineering and manufacturing change management*." To reach this, we started with reviewing the state of engineering change management, manufacturing change management, and additive manufacturing research topics. Giving a synopsis of Chapter 2, we can note an insufficiency of research on integrated quantitative analysis of engineering and manufacturing operations, especially when studying the associated transformations brought by AM. Particularly, we have identified three research gaps (RGs) that are critical for developing either domain separately or in combination with another, as in this work. Based on these gaps, summarized in Table 2.4, we formulate the research objectives (RO), serving as high-level guidance in developing the potential solution. Ultimately, we define the primary **research question (RQ)** of this work, aiming to formulate it as clear, unspecific, answerable, and value-free (Blessing and Chakrabarti, 2009):

RQ *How to drive a techno-economic improvement of the additive manufacturing-based product creation practice through integrated change management between engineering and production?*

It is important to clarify that this thesis considers a product creation environment having the capability and capacity – in terms of the organization, workforce skillset, infrastructure, and experience – necessary to conduct the ECM (section 2.1.2) and MCM (section 2.1.3) procedures, and also operate at the fourth level of AM adoption, described in section 1.2. The following sections, i.e., Chapter 3-Chapter 6, are devoted to a comprehensive response to this question. However, though this RQ concisely states the purpose of this work, being formulated as an open question, it requires specification to be addressed effectively. Therefore, based on the discussion in Chapter 1-Chapter 2, Table 2.4 specifies the question focusing it on various aspects of the Design Research, as discussed by Blessing and Chakrabarti (2009). Notably, the research sub-questions (RSQ) point at the challenges related to understanding and supporting the issue regarding the facets of design research, being people, product, methods, tools, organization, knowledge, micro-, and macro-economy. The next chapter addresses the first research objective to set the stage for framework realization in Chapter 4.

Table 2.4. Research gaps, objectives, and sub-questions.

Research Gaps	Research Objectives	Research Sub-Questions
RG-1 (p. 27): Appreciating the importance of tight collaboration between engineering and manufacturing change management teams, this work emphasizes an immaturity of the integrated change management conception. It lacks the definition and the reference process enabling its practical applicability. Furthermore, there is a lack of explicit methods suitable for quantitative analysis of the integrated change management practice, which can be applied to explore the efficient case-specific process architectures. Given the importance of accurate estimations, such methods should provide the means for the reduction of uncertainty inherent to PD activities planning.	**RO-1.1:** Elaborate the notion of integrated change management (ICM) by introducing its definition and detailing its reference process.	**RSQ-1.1:** What are the critical elements of the ICM notion that its definition shall cover?
		RSQ-1.2: Which stages shall an ICM reference process have?
		RSQ-1.3: What are the major interconnections within the network of ICM steps?
	RO-1.2: Develop an analytical framework enabling an accurate quantitative assessment of the time and cost performance of a given ICM process architecture.	**RSQ-1.4:** Which characteristics of the ICM process architecture shall the framework be able to assess quantitatively?
		RSQ-1.5: What kind of methods and tools shall comprise the framework to enable the assessment of the necessary architecture characteristics?
RG-2 (p. 42): Evaluating the potential of AM technologies and LPBF, in particular, to reshape the product lifecycle by, foremost, enabling the production of functional end-use components with unavailable before complexity and customization, this work recognizes a lack of analytical model-based methods enabling quantitative assessment of Additive Manufacturing impact and providing a detailed consideration of production planning issues.	**RO-2:** Develop an analytical framework that captures a complete LPBF process workflow and considers the related production planning issues in studying its techno-economic performance.	**RSQ-2.1:** What kind of transformations does AM bring to the product creation process when considered as a technology for the production of functional end-use components?
		RSQ-2.2: What kind of cost constituents an accurate analytical framework shall address when studying an AM-enabled production?
		RSQ-2.3: Which factors shall the framework study to cover an entire design space for an AM-enabled manufacturing system?
		RSQ-2.4: What kind of methods and tools shall comprise the framework to efficiently and accurately study an entire shop floor design space?
RG-3 (p. 45): There is a lack of the modeling frameworks that could capture the engineering and manufacturing domains in integration to conduct quantitative techno-economic analysis of the managerial decisions associated with planning the product creation process, especially in the context of AM-enabled production.	**RO-3:** Provide integration of the framework elements for the combined study of the PD and manufacturing planning issues in the AM context.	**RSQ-3.1:** What kind of linkages between the engineering and manufacturing domains shall have an integrated framework?
		RSQ-3.2: What are the advantages and disadvantages of an integrated engineering and manufacturing planning approach?

Chapter 3

Developing an understanding of integrated change management in the Additive Manufacturing context

This work aims to advance engineering and manufacturing research fields by addressing a multifaceted task: provide an instrument that can quantify the influence of various engineering and production planning decisions in the additive manufacturing context. It is essential to recognize the objective's complexity, as it contains “many elements or entities that are highly interrelated, interconnected, or interwoven” (Crawley, Cameron and Selva, 2015). However, if addressed properly, the systemic view on this interdisciplinary subject should yield an emergence of a novel analytical capability, which would not be achievable by the individual analysis of any linked research topic. This anticipated capability is exactly the reason for looking at the subjects in an integrated manner, and it requires a comprehensive grasp of all related areas. For this, using the system thinking model of thought, we can first employ decomposition as a tool to “divide and conquer” the complexity. When the relevant subjects are addressed to an appropriate extent, we will be able to proceed with the integrated analysis.

Out of the literature review in Chapter 1-Chapter 2 and as illustrated by the first level of the objective decomposition in Figure 3.1, we can recognize that at a high level, the stated task involves the analysis in several groups of research fields. The management of engineering and manufacturing changes forms the basis for integrated change management (ICM). Hence, it must cover all changes to the product and its development process and organization, including the manufacturing system. Then, all those fields exist within the studies on product creation practices. From a separate domain, an introduction and advancement of the novel production methods bring the influence of AM in the discussion. Going to the second level of decomposition, we can specify the subjects to consider when developing the objective solution. It shall be capable of supporting a quantitative assessment of different planning and execution decisions related to engineering and manufacturing activities, such as those discussed by Krishnan and Ulrich (2001). It also shall consider the decisions on manufacturing system design, such as the specification of the constituent equipment or its layout. These aspects shall become the variable parameters when studying the ICM process using a to-be-developed instrument. Along with that, the current study shall address the particular impact that AM will have on the ICM process. To derive such evaluations, it would be necessary to first determine the general transformations in the product creation process triggered by AM.

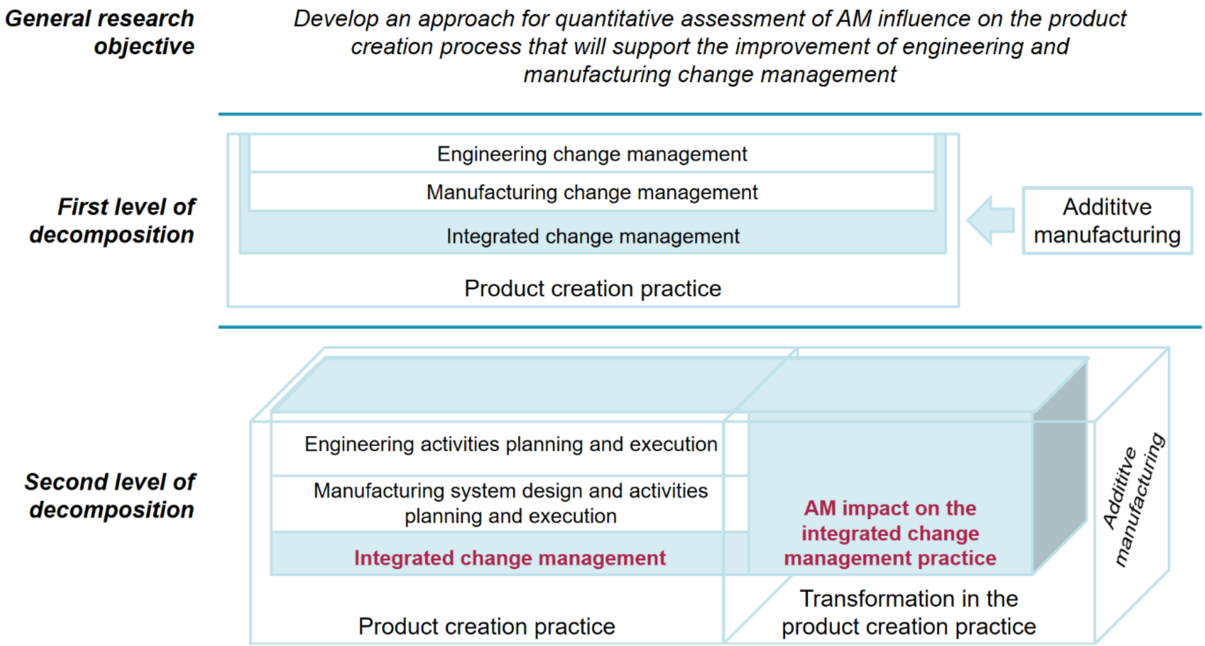

Figure 3.1. Decomposition of the research objective into the related research fields.

Following the logic of decomposition, this work starts with understanding what integrated change management is and what is the influence of AM on the product creation process. It is necessary to address these topics in the first place to proceed with the quantitative analysis on the topics of the second level of decomposition. Based on the definitions and reference processes for engineering and manufacturing change management, section 3.1 elaborates an ICM conception, addressing by this RSQ-1.1 – RSQ-1.3. It lists its major elements and shows the key interrelations between them. Then, section 3.2 focuses on RSQ-2.1 by presenting the results of a qualitative interview-based study on AM-enabled product development and manufacturing. The solutions for numerical studies are discussed in Chapter 4.

3.1 Integrated change management

As stated in section 2.1.4, this work is inspired to elaborate the integrated change management concept and thus establish a deeper integration of the engineering and manufacturing operations. Therefore, we need an in-depth look into the interrelations between the engineering change management (ECM) and manufacturing change management (MCM) processes. According to Jarratt, Clarkson, and Eckert (2005), engineering changes (ECs) can originate at any stage between the high-level design of a system and its serial production, as shown in Figure 3.2. To manage ECs, i.e., ECM, means to organize and control any alterations to products introduced between these phases. Though not specified by Jarratt, Clarkson, and Eckert (2005) or Wickel *et al.* (2015), handling an EC would also involve implementing the necessary changes in manufacturing. For example, the high-level ECM reference process by VDA 4965 (2010c) marks the change implementation in manufacturing as a separate phase, as illustrated in

Figure 2.3. It is important to note that there is a good chance that a product alteration would trigger the manufacturing changes (MCs).

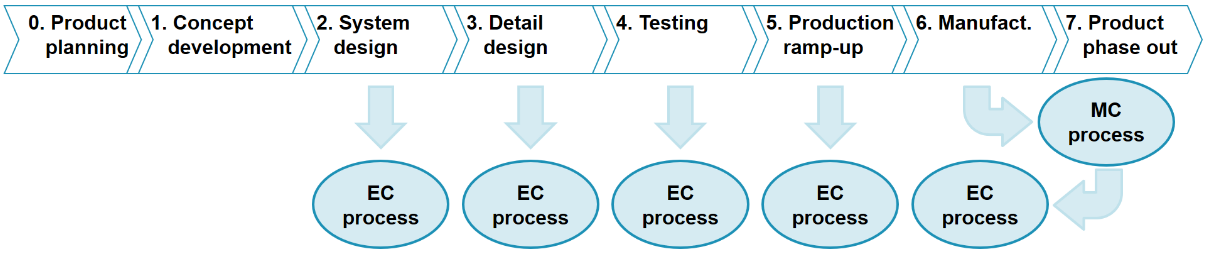

Figure 3.2. Possible phases of the product creation process at which the engineering changes can occur; adapted from (Jarratt, Clarkson and Eckert, 2005).

However, the MCs can also occur for other reasons, such as the launch of a new product on an existing manufacturing line or an increase in production volume (section 2.1.3 lists the variety of MC causes). This, in turn, creates the probability for the other ECs, triggered by the production side, as shown with phase 6 of Figure 3.2. Similarly to ECM, MCM means organizing and controlling any alterations to manufacturing, i.e., either to an established manufacturing process or to a current layout of a production system (Koch, Michels and Reinhart, 2016). We can see how tight the connection between the ECs and MCs is and the parallelism of the ECM and MCM processes. Therefore, as stated in section 2.1.4, integration between these processes is necessary to minimize the risks of disconnected and, therefore, poorly coordinated management of the changes across two domains.

Similarly to a medical field definition, integration in engineering would attribute to "the combining and coordinating of separate parts or elements into a unified whole" (*Integration | Definition of Integration by Merriam-Webster*). With that perspective, this work proposes the following definition of *Integrated Change Management* (ICM):

> ***Integrated Change Management*** *is organizing, controlling, and executing the process of making changes or modifications to the released structure, behavior, function, or the relations between functions and behavior, or behavior and structure of a technical artefact, and its manufacturing process, and its manufacturing resources, using the integrated framework, that connects all involved stakeholders and the digital definitions of a technical artefact, manufacturing process, and manufacturing resources.*

The presented definition aims to incorporate all the elements related to the management of engineering and manufacturing changes. Therefore, it blends the definitions of EC, ECM (Jarratt, Clarkson and Eckert, 2005; Hamraz, Caldwell and Clarkson, 2013), MC, and MCM (Koch, Gritsch and Reinhart, 2016; Koch, Michels and Reinhart, 2016), and also adds more emphasis on the manufacturing resources. This work believes that integrating these parts is critical to comprehensively managing all engineering and manufacturing changes within the product creation process. When one coherent system handles the ECs and MCs, it will provide an emergent function unavailable in separate ECM or MCM execution. This function attributes to the efficient coordination of the change data across all product creation activities and, hence, increases the PD system's potential for optimal planning and expenditure of the available resources.

To provide such integration, a product creation system must operate on a commensurately integrated data structure and must possess and maintain the necessary interfaces streamlining cross-domain information transfer. This means that an ICM concept needs to highlight the major interconnection channels between ECM and MCM. For that, this work combines the ECM and MCM references processes within a shared framework and introduces a corresponding ICM reference process.

Furthermore, to vividly illustrate a proposed idea, this work uses a specific project as an example. Its purpose is to complement the abstract elements of the ICM concept with the explicit expressions of the intended meaning and thus point up the inter-domain interfaces. Particularly, the explanation of ICM will be done around the Skoltech research project devoted to the development of the deployable unmanned aerial vehicle (UAV). The details of the project are available in (Nikolaev *et al.*, 2018). The scenario is based on the change in the UAV functional requirements: to increase the system's thrust, the project team reviews the design change options to the UAV propulsion system, as shown in Figure 3.3.

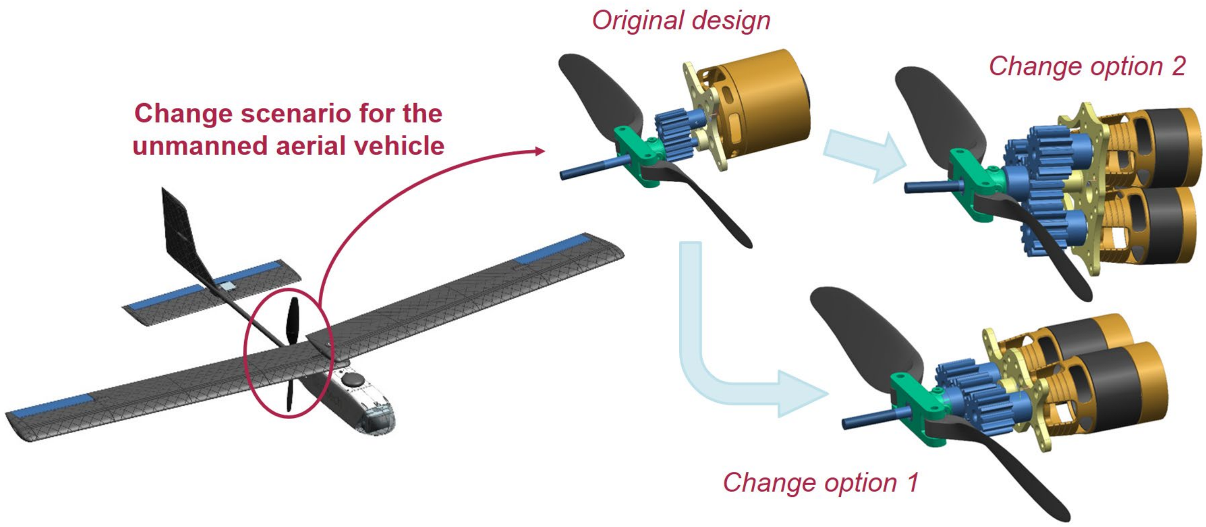

Figure 3.3. Change scenario for the unmanned aerial vehicle[27].

In response to the given change request, the whole product creation system needs to go through ICM. Perceiving the ICM process as a system of activities and interrelations, the development of its reference

[27] Credit to Daniil Padalitsa (Skoltech) for providing the CAD drawings of the product.

process starts with the stakeholder analysis following the systems engineering approach (Library and Administration, 2017). To identify all related stakeholders of the system and their expectations, this work asks the following question: which groups or individuals are affected by or somehow influence the project's objectives? Answering it, we can derive the following list of stakeholders:

1. *Product Development* department, which is responsible for product design and implementation of changes in the engineering domain.
2. *Manufacturing Engineering* department (ME), which is responsible for product manufacturability analysis, development of the manufacturing processes, definition of the production system design, and implementation of manufacturing changes.
3. *System Manager* or *Project Manager*, who is coordinating and controlling the change development and implementation in line with the ICM vision; this role maintains the system architecture, data structure, and the change management policy.
4. *Inspection and Testing* department, which is responsible for inspection and testing of the product, manufacturing processes and the system, commissioning, tests' reports generation, verification and validation of the product, processes, and resources.
5. *Logistics* department, which is responsible for communication with suppliers, design of inbound and outbound material flows, and operations scheduling.
6. *Shop Floor Operation* department, which is responsible for manufacturing system planning, control, and operation.
7. *Suppliers*, which supply the necessary components and resources, such as the assembly components, energy, water, tooling, compressed air, software, etc.
8. *Customer*, which formulates the product functional and design requirements.
9. *Sales and Marketing* department (SM), which is responsible for market analysis, cost definition, and communication with the *Customer*.

Having the stakeholders identified, we can create the ICM process structure, relying on the reference processes for ECM and MCM discussed in sections 2.1.2-2.1.3. As shown in Figure 3.4, the major stages of ECM and MCM are laid out along with each other in the arrangement necessary to indicate the significant interconnections. The stakeholders are shown in the rectangle boxes containing the representative roles. Then, based on this high-level view of the ICM process, we can arrange the main steps performed in the engineering and manufacturing domains, as illustrated with the ellipses in Figure 3.5. Moreover, to close the loop with the customer, we complement the taken ECM and MCM reference processes with an additional step during the concluding change evaluation and control stages: validate the change with the customer.

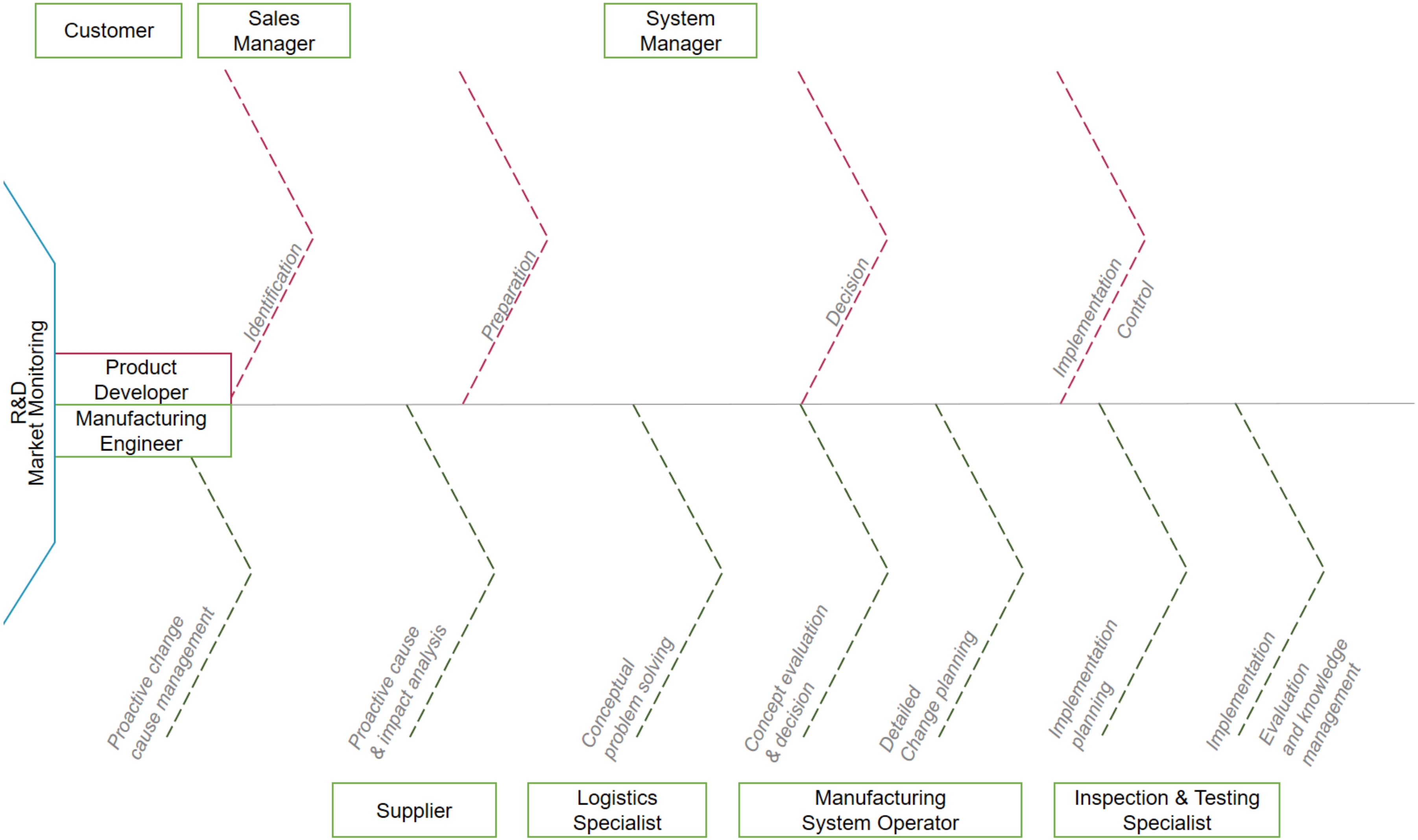

Figure 3.4. A generic ICM process structure that covers the ECM and MCM phases and displays the major stakeholders of the product creation system.

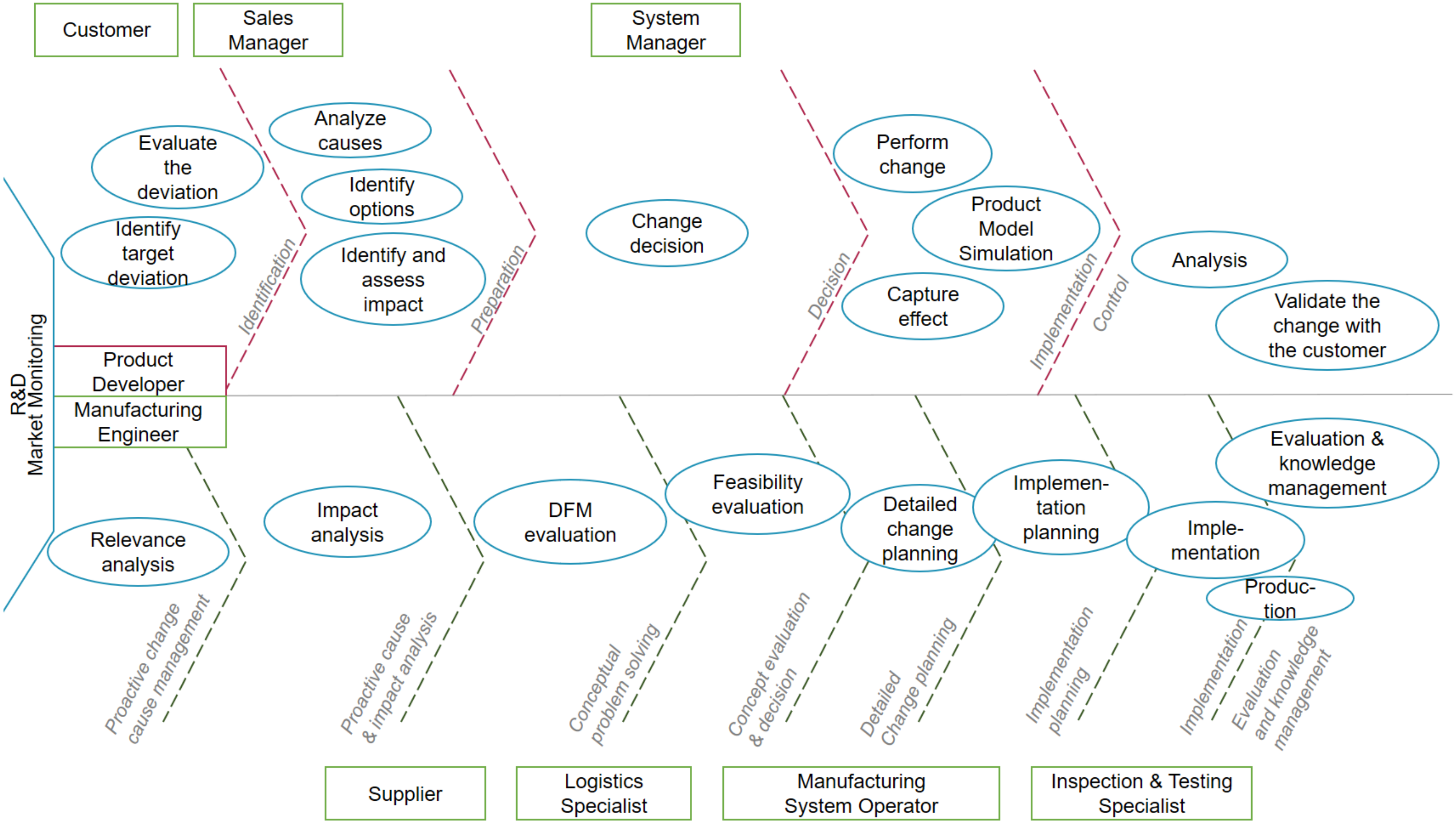

Figure 3.5. Main activities within the ICM process.

Now, when the ICM process's content is defined, we can conceptualize the given change scenario and identify the interrelations between the ECM and MCM activities. Figure 3.6 shows the final state of an animation, which illustrates the change propagation step by step[28]. To underline the importance of interdisciplinary decision-making, the scenario uses the Quality Gates, represented by a traffic light with a set of specific requirements. It is necessary to meet a given set of requirements to pass the gate (Koch, 2017).

The change scenario develops as follows (the list numbers correspond to the numbering in Figure 3.6):

1. The PD and ME departments proactively investigate potential change causes, where the R&D activities for an internal search within the company, and market analysis for an external search.
2. Customer requests the change of the product requirements; e.g., increase the payload of the UAV.
3. The PD department identifies the design's target deviation, and the ME team investigates the relevance for manufacturing changes.
4. The SM and PD departments collaboratively create the product design change request, following the customer needs.
5. The PD department evaluates the deviation and analyzes the product design change propagation.
6. If the design change is necessary, the PD department analyzes root causes that have motivated the Customer to change the requirements.
7. The PD department identifies the options to solve the problem; e.g., it evaluates the change possibilities in the aircraft aerodynamic scheme, materials, or design.
8. The PD department develops the engineering change concepts (ECCs) based on the chosen solution options.
9. The PD and ME departments assess the impact of implementing the design change concepts from the respective perspectives; the concepts are further developed through the loop of steps 3-9.
10. The PD department selects an ECC.
11. The PD team reaches the quality gate, which will open when the PD and ME teams agree on the preliminary manufacturing feasibility of the concept solution.
12. The ME department creates the manufacturing change request (MCR) based on the chosen ECC.

[28] The animated version is available at tiny.cc/ICM_scenario (accessed on June 30, 2021).

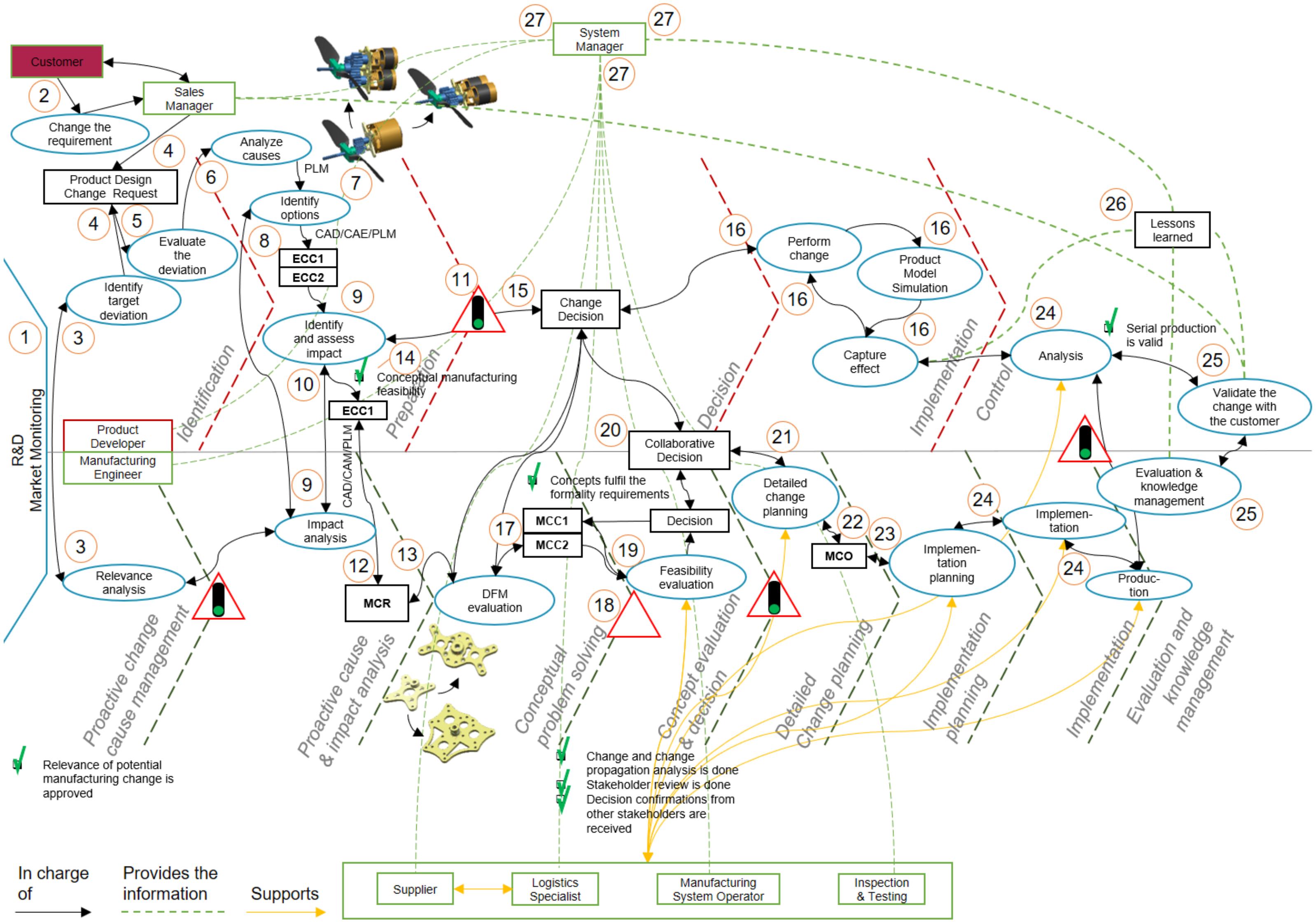

Figure 3.6. The final state of the ICM process initiated by the customer's request to change product requirements.

13. The ME team analyzes the developed design of an ECC for manufacturability (DfM).
14. When the ME department approves the conceptual manufacturing feasibility, i.e., it confirms that the current or to-be-modified manufacturing system would be capable of producing the chosen design concept, it opens the gate for the PD team towards the change decision. If the chosen ECC is infeasible, then the process returns to step 9.
15. Having a confirmation of the ME department on the preliminary manufacturing feasibility of the concept solution, the PD department passes the Quality Gate and proceeds to the design change decision. The ECC review process derives the decision in the form of a document, which is therefore represented as a rectangle instead of the ellipse.
16. The PD team performs the detailed design of the change, simulation of the necessary mechanical studies, and analyzes the results.
17. The ME department evaluates the developed design and prepares the manufacturing change concepts (MCCs).
18. The MCCs must fulfill the company's formal requirements, which are represented by the warning Quality Gate, i.e., without the traffic lights.
19. The ME team, supported by other stakeholders' input, conducts the manufacturing feasibility evaluation of the developed MCCs and arrives at the corresponding decision.
20. For the ME team to carry out the detailed design and implementation of the manufacturing change, the PD and ME departments must come to a collaborative decision on the product design change. This condition is necessary to avoid future unplanned manufacturing changes, which can be expensive as the change implementation in this domain involves the steps of procurement and production process implementation. This collaborative decision shall be based on fulfilling the requirements of one of the most critical Quality Gates with three checkpoints:
    a. The design change and the change propagation analysis are completed.
    b. The feasibility reviews by the stakeholders are completed.
    c. Decision confirmations from all stakeholders are received.
21. The decision would either let the ME department and supporting stakeholders proceed to the next steps or return the PD and ME teams to product design, i.e., step 15.
22. Upon completing the MC detailed design, the ME department releases the manufacturing change order (MCO).
23. The MCO triggers the implementation planning with the support of the related stakeholders.

24. During the MCO implementation, the production starts to ramp up. The Quality Gate does not allow to approve the ME deliverables until the production runs stable in the changed configuration. At this phase, the potential change propagation to design or other related stakeholders is handled through the backward connections and close collaboration between the PD and ME teams.
25. Once the gate is open, the change implementation completes, and the change result is passed through the Sales and Marketing department to the Customer for the validation.
26. If the validation performed by the Customer is successful, then the change is complete and the "lessons learned" are documented. If the change does not pass Customer's validation, then the process proceeds with backward iterations through the "Analysis" step (24).
27. The stakeholders analyze the lessons, aiming to improve their operation in the future ICM processes.

From this demonstrative scenario, we can see that the ECM and MCM processes are intertwined in three main places, as emphasized in Figure 3.7. The first inter-domain collaboration happens at the early stage, where the EC concepts, developed by the PD team, need to go through the preliminary manufacturing feasibility analysis. It needs to be done before the PD department would invest the resources into the detailed design of the change and pre-commit the major part of the budget (see Figure 2.1) and before the ME department would begin the work on the conceptual solutions. Teamwork at this point creates the first filter discarding the impracticable or over-expensive solutions. The second and maybe the most crucial point of collaboration takes place right before the detailed design of the selected MC. After the PD team creates the detailed design of an EC and before finally committing the manufacturing implementation costs, the ECM and MCM teams, in concert with the supporting stakeholders, cooperatively decide on the EC design freeze. This resolution is necessary to avoid costly manufacturing-to-engineering iterations at the latter stages of the ICM process. During the implementation of the MC, we can mark the third phase of interconnected work. Since there would still be a chance of the backward rework loops from manufacturing to engineering, the PD and ME departments need to continue close teamwork to select the optimal change design decisions and minimize the expenditures.

Altogether, these inter-domain collaboration points are necessary to review the decisions that define how the project commits the costs and expends them. Therefore, the quantitative assessment of the corresponding engineering and manufacturing planning decisions will happen within those connections using a developed solution (Chapter 4). However, it shall be noted that the ICM procedure's better performance in terms of quality of the generated ideas might require different degrees of inter-domain integration in different cases. Depending on the application or an industry sector, the firm might need to adjust the extent of integration between the PD and ME teams at the particular ICM phases.

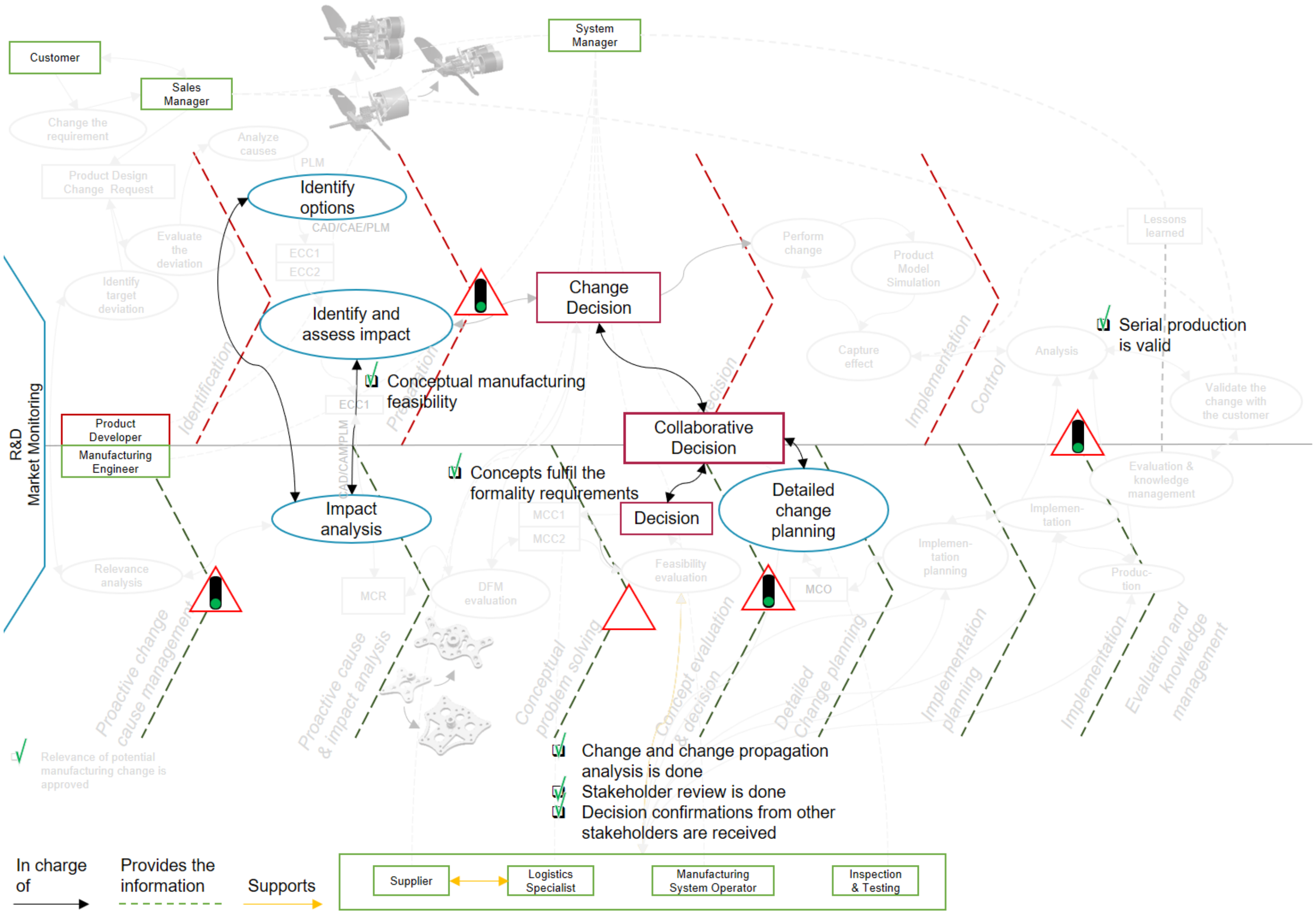

Figure 3.7. The major phases of ICM inter-domain collaboration.

The reason is that a deeper in-house collaboration creates more design constraints for both domains. Having more restrictions can overcomplicate the PD system and reduce the design freedom necessary to create innovative solutions. Nevertheless, the general objective pursued by the definition of an ICM reference process – i.e., the minimization of the change time and cost expenditures – also minimizes the cost of opportunity. If the integrated change lasts less and requires fewer resources, it supports the entire PD project in allocating the remaining assets for the other needs.

This work uses the rationale and the arguments presented above to address the research questions RSQ-1.1 – RSQ-1.3 and elaborate the ICM concept, its structure, and the primary interconnections between the engineering and manufacturing operations. Further, to address the other research questions, we add the context of additive manufacturing (AM) in the discussion. As pointed with RSQ-2.1, this work researches ICM from the viewpoint of the transformations brought by AM. Notably, it tries to bring more clarity in what we can see different in PD operations – and ICM as part of them – using AM as the primary production method. Section 3.2 describes a separate study undertaken to answer the RSQ-2.1.

3.2 Understanding the transformations in product development brought by Additive Manufacturing

Numerous examples are showing how additive manufacturing (AM) technologies revolutionize the PD and manufacturing operations. If we look at the generic product creation and tracking process proposed by Pahl *et al.* (2007), we can see that AM has already influenced each phase of it. As shown in Figure 3.8 and partially discussed in section 1.2, AM expands the design space and thus creates new market opportunities, improves the user experience, and facilitates the spare parts' on-demand supply. The latter is also enabled by the digitalized nature of the 3D printing processes, which, moreover, shortens the design-test cycles and enables rapid prototyping. At the shop floor, AM allows engineers to prepare the necessary tooling and assembly fixtures multiple times faster, and hence further shorter the overall cycle. The advancement in printing quality, i.e., in the resulting material homogeneity, strength, and hardness, of both polymer and metal printing, has enabled the serial AM. It gives the firms an opportunity to access novel design solutions that increase the performance characteristics or decrease the production costs. Finally, AM prolongs the overall lifecycle by widening a range of possibilities in product restoration, and thus extending the product operation phase and postponing the recycling phase. Furthermore, when the product eventually reaches a concluding lifecycle stage, AM promises to support the recycling methods and reuse such material as polymers, composites, and metals, albeit the cost-efficiency and the technological difficulty of this are still high (Peng *et al.*, 2018; Narra *et al.*, 2020).

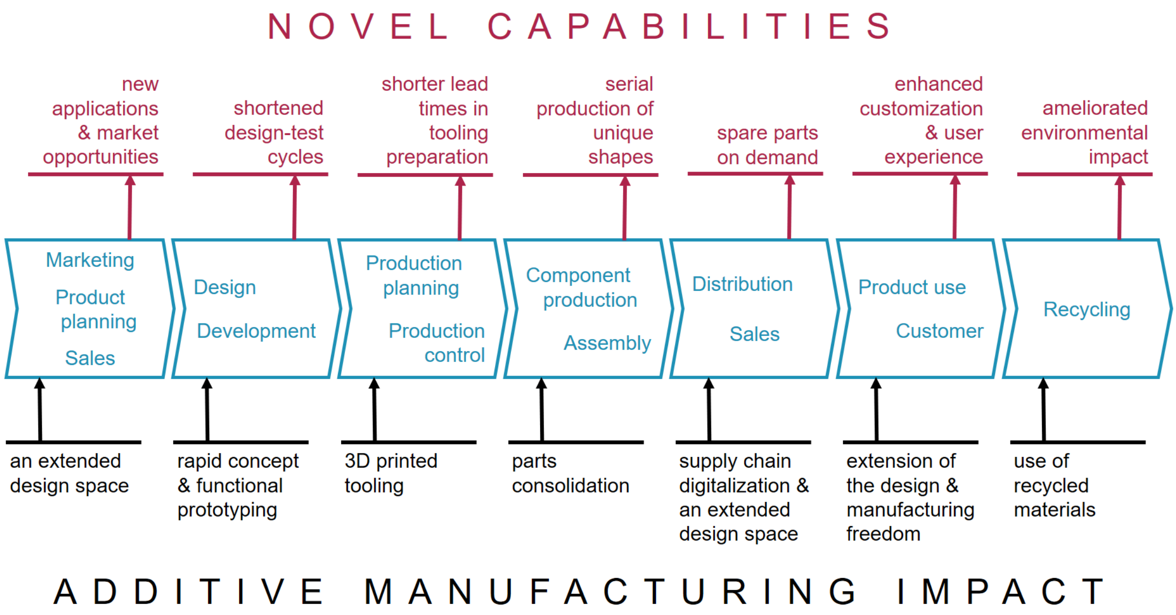

Figure 3.8. The impact of AM yields novel capabilities throughout the whole product creation and tracking process that is adapted from (Pahl *et al.*, 2007).

However, in more strict terms, the listed capabilities have been evidenced in practice but do not express it in full. They indicate the AM's potential to transform the product lifecycle rather than reflect the current reality. At present, many 3D printing methods do not possess the technology readiness level (TRL) necessary for its reliable use – e.g., see the cross-industry comparison of the laser powder bed fusion (LPBF) technologies in (Schmidt *et al.*, 2017) – and therefore do not provide a desired stability of the processes. Given this relevant immaturity of the AM technology, its recognized presence, which we can perceive as an average capacity and capability of companies to exploit AM at a given PLM phase, is not yet as uniform and extensive as that of the conventional manufacturing processes.

Aiming to close the gap, this research includes an exploratory empirical study of AM's influence on the product creation and tracking process. As part of the three-year "Work of the Future" initiative[29], the

[29] In spring 2018, the Massachusetts Institute of Technology (MIT) had launched a three-year initiative named "Work of the Future." Its primary goal was to investigate the influence of the machines with "human and superhuman capabilities" on the skillsets necessary for the prosperous future of work across a variety of industries. The initiative has included five projects devoted to (1) the global adoption of emerging technologies; (2) mutual support between the institutions and organizations while adapting to the change; (3) transformation of the mobility and transportation sector; (4) educational and training support; and (5) the impact of the advanced manufacturing methods on an entire product creation process. A part of this thesis devoted to analyzing the AM impact has been conducted within the scope of the Advanced Manufacturing project (5) under the supervision of Professor A. John Hart. The web page of the project is available at: https://workofthefuture.mit.edu/.

author and colleagues from the MIT Mechanosynthesis group[30] have conducted an interview-based case study with a large energy sector manufacturer. The Company is among the pioneers in adopting AM for volume production of the functional end-use components. Within three days on-site, our team has interviewed 14 Company employees at the design, production, and executive positions, which have participated in the project of study. The case represented a re-design and manufacturing of a 13-component metal product – previously produced via conventional methods such as casting, milling, and welding – into one consolidated part to be produced using the LPBF technology. Specifically, this study addressed the following research questions[31]:

1. What kind of changes in terms of work effort (type, intensity, duration) can be observed when mapping and juxtaposing the product development cycles with conventional and additive manufacturing practices (including design, engineering, and production)?
2. What kind of implications does such transition have on requirements for roles, tasks, skills, manufacturing facilities, equipment, supply chain, etc.?
3. How does additive manufacturing affect the expenditure of resources, such as materials, energy, engineering hours (including manufacturing, logistics, machine operating hours), and the cost of software used?

The interviewing method and the results are described in the following subsections.

3.2.1 The method of interviewing, data collection, and processing

To collect the qualitative and quantitative data on the project, our group has taken the approach based on semi-structured interviews instead of more strict interview- and survey-based methods confined by the standardized templates. The chosen technique covers the opacity of prior case-specific knowledge to the interviewers as it leaves the space for the conversation to follow any emerging trajectory. Such adaptability has been chosen to ensure a respondent's freedom in telling the stories, i.e., case descriptions with the subjective interpretations, which are perceived to be the richest form of sharing the information (Silbey and Perdue, 2018). The interviewing process's flexibility is considered to be important for collecting as much critical and relevant information to the AM-triggered transformation as the respondent deems. Furthermore, we posed the questions in a way that allows the interviewee to take any side of a controversial issue.

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[30] The on-site interviews have been conducted together with Haden Quinlan and Kaitlyn Gee. The interview transcripts have been analyzed together with Haden Quinlan, Kaitlyn Gee, Philipp Oehlschlaeger, and Gregory Dreifus. The web page of the Mechanosynthesis group is available at: https://mechanosynthesis.mit.edu/.

[31] The research questions' formulations are given in a form they have been submitted in the application for a comprehensive review to the MIT Committee on the Use of Humans as Experimental Subjects (COUHES).

However, to allow the subsequent coding and comparison of the collected data with the future case studies, we have based the method on a generic interview protocol given in appendix A3. It prescribes the major stages of the interview session, being the introduction, open conversation, revision, and wrap-up. At the introduction, both sides familiarize themselves with each other, after what the interviewers describe the research purpose and sign the consent form[32] with the interviewee. At the second stage, our team posed the open-ended questions, prompting the subject to offer the specific information and paths for further exploration, thus providing the context for the follow-up precise questions. At the revision stage, we asked detailed questions to provide the quantitative values for data collection or elaborate on previously asked questions. At the final stage, the subject is offered an opportunity to provide any additional information he or she considers valuable to the study. The protocol also includes a common set of open questions for each stage, which are devoted to identifying the respondent's role and background, clarification of the product development practice, measurement of the AM effects, and transformations in the necessary skillsets observed during the deployment of the technology.

During each hour-long session, two interviewers have been taking the typed and hand-written notes correspondingly, whereas the third interviewer has been leading the discussion. This way, the approach ensures that the team keeps the interviewee engaged in the development of the conversation, as well as provides the necessary means to document the data in the narrative and graphical forms when needed. Out of 14 sessions, we have received circa 1200 responses to process and synthesize into specific findings.

To analyze the interview transcripts, we have adopted the method described by Burnard (1991). The first step was to compile all field notes into an integrated collection of records. The documents then went through a first screening to identify the general themes and immerse the team in the data. Based on that and by re-reading the transcripts as many times as necessary, one team member has derived an array of categories, i.e., open coding, that captures all useful information. Next, the same member has clustered the categorized information into the groups and revised them to remove any repetitious or

[32] The MIT Committee on the Use of Humans as Experimental Subjects (COUHES), which acts as the Institutional Review Board (IRB) for research involving human subjects, requires to receive the documented consent from all respondents before proceeding to the interviewing process. It includes the description of the study, its terms, subject name and signature, a signature of the person obtaining informed consent, and the contact details of MIT COUHES. Alternatively, the interviewee can sign a waiver or alteration of informed consent request. Also, following the COUHES regulations, to conduct the research involving all types of interactions with human subjects, each investigator has been certified through the Basic Course on Human Research within the Social and Behavioral Research Investigators Group from the Collaborative Institutional Training Initiative (CITI program). The details of the COUHES regulation are available at: https://couhes.mit.edu/training-research-involving-human-subjects.

highly similar codes. Except for the first one, the listed steps have been iterated independently by two other team members, without seeing others' lists, attempting to protect the study against researcher bias. Then, the different categorization schemes have been discussed and synthesized into one system. Furthermore, the final coding architecture has been revised for consistency with the AM implementation framework proposed by Mellor, Hao, and Zhang (2014).

At the subsequent analysis phase, we have coded – and color-coded, i.e., highlighted the distinct sections with the respective colors – all responses using the developed categorization system, allowing for additional adjustments to the coding structure if it does not cover useful information. The resulting architecture of classification included five main categories: AM Technology, System of Operations, Organizational Change, AM Supply Chain, and AM Strategy. Altogether, they had 19 sub-categories and contained 160 discrete codes overall. Finally, we have reorganized the responses by extracting each coded section and putting it along with the list of categories. When doing that, we kept all the words necessary to save the context of the statement and made a reference on its origin in the transcripts to track back to it if anything would appear unclear.

Using a list of responses reorganized around the developed categorization system, our team has written the case study report. We stayed open to refer to the initial transcripts during this process to ensure a strong reliance on the original meanings and contexts (Burnard, 1991). Based on the "System of Operations" category, the next section describes the significant findings on the alterations in the product creation process triggered by AM.

3.2.2 Significant findings on the AM-driven transformation of the product creation process

The adoption of AM technology implies not only the change in the production process but also in the entire product creation and tracking process, as it was immediately declared by the CEO of the Company's branch operating in the energy sector. In 2005, the team responsible for introducing AM in the Company's product creation operations consisted of three people. Taking the trial and error approach, they started to adopt the technology and work on a novel AM-specific PD process, which was not wholly formalized 15 years later, according to the respondents. This is because the field's immaturity and ongoing, or even accelerating, development induces uncertainty and forces the Company to revise its implemented solutions continuously.

In the project of study, the Company started with modification of a conventionally-produced assembly following the traditional design workflow. With respect to the stages of product planning and concept and detail design, the respondents noted a considerable influence of the design space expansion. The realization of this new potential required a shift in the mindsets of both management and engineering personnel. The former needed first to acknowledge a substantial research component of AM introduction and then become supportive in exploring the unimaginable before designs. It was necessary to develop an entrepreneurial spirit in the latter by encouraging failing fast and cheaply, even though it signified higher prototyping expenditures with thousands of USD per build. On the other hand, the engineers needed to become open to the change and also reinforce collaboration between the product and AM process designers.

Presumably, as a result of that, many respondents have recognized an acceleration of the design-prototyping cycles when compared with the preceding casting-based alternative of the process. The subjects attributed this to many reasons. The first is related to reduced temporal and economic implications of re-design iterations on the failed prototypes, leveraging the process's digitalized nature. Tightly connected to this, the second factor builds on eliminating the need to design the custom tooling, which can have a lead time of up to one year. This further decreases the time, cost, and risk of re-work. Another reason assumed by several respondents is a simplified part performance analysis: the AM's rapid prototyping capability allows to conduct the physical tests instead of the simulations, which can be highly complicated and lengthy for the complex systems. However, at the same time, in some cases, the AM-based prototyping can take longer than with traditional manufacturing methods due to the lower reliability of the process and the complexity of generating an optimal support geometry.

In addition to that, the respondents note that AM allows to study a variety of prototypes earlier in the process and thus facilitates the exploration of the design space. Also, given the prototyping agility, the design freeze can be done later in the process. Such capabilities seem to be critical enablers in accurate navigation within the design tradeoffs suggested by the set-based design (SBD) principles (Sobek II, Ward and Liker, Jeffrey, 1999; Toche, Pellerin and Fortin, 2020). Overall, in the current case study, the listed above benefits for the PD process appear to outweigh the delay caused by a critical need for components' thorough validation due to technology's immaturity at the production scale.

Further, when reviewing the AM's impact on the production stage, the respondents highlight a reduced interval between product design and the start of the manufacturing process. Besides the above factors, they attribute this to a fast fixture preparation using a dedicated 3D printer. However, there are a number of challenges the Company faced while establishing the volume production, which have decelerated the process on the other hand. Since it is difficult to make the standard printing parameters work with arbitrary geometries, the process often requires customization and re-qualification. Another impediment stems from the need to grow an in-house AM-specific production planning expertise. The Company initiated it as an R&D effort, which then ripened to a separate sub-group lead by a newly defined AM planning and logistics manager's role. This team was tasked with developing a novel scheduling and planning process in close coordination with the other departments, such as the product and process design groups. For example, the post-processing operations can take up to 70% of the overall shop floor efforts; therefore, each AM part must have a specific post-processing plan. These operations are executed either in-house for the spare parts and prototypes or by outsourcing the components to the casting partners, taking the benefit of similar finishing requirements. These plans usually take about one week to confirm.

These alterations in the product creation process influence the distribution of responsibilities and the interactions among various roles. First, by making a transition from outsourced casting to in-sourced 3D printing, the team has enhanced the communication between the designers and the AM-related roles. A key example of this is immediate feedback from the post-processing to design stages informing the efficacy of a chosen engineering decision. If re-design is necessary, this linkage is drastically expediting it. A person responsible for digitalization in AM has even expressed an opinion that the design for AM expertise should come from a production-oriented rather than an R&D role. It underlines an intensified connection between design and manufacturing for AM. However, in this case, a highly influential factor that strengthens the interaction between the different roles might be a local culture. As pointed out by the respondents, apparently, its openness facilitates discussion between the employees of various expertise and positions within the Company's hierarchy, e.g., pushing the operators and technicians to discuss the design decisions with the PD team. Similarly, AM and test engineers have extensive involvement in the design process. Moreover, AM prototyping speed encourages all employees to experiment, which is vital for an exhaustive exploration of the design space.

To additionally support the connection between the design and manufacturing engineering activities, the Company has introduced the AM technician role that will work on reconciling the objectives of two domains. This position requires a solid background in both design and AM process operations to find intermediary multi-objective solutions. For example, a person would need to adjust the part geometry to ease support generation and minimize their overall volume, thus aiding both the printing and post-processing activities, as shown in a case study by Meisel *et al.* (2017). This need of the design for AM (DfAM) expertise puts high qualification requirements on the personnel, seeking those who combine the design, engineering, and manufacturing experience (see the summary of DfAM challenges in section 2.2.3). Therefore, this work will attribute AM *technician* to the AM *technologist* role, indicating a broader scope of competencies than only servicing the machines. In general, the Company distributes product engineering and analysis activities: the AM technologists simulate the build process, whereas R&D personnel looks into the components' material performance.

The management responsible for introducing the technology acknowledges the privilege of benefiting from having a small and multifunctional AM team, which is successful for cooperation. Nevertheless, to grow the AM capability and capacity, the technology-driven PD process needs to be standardized. There is currently a checklist to go through before the AM production runs within a design-test loop. Such an approach formalizes and stabilizes the process with the rigid sequence of the review gates; however, the latter also makes it less agile and can deteriorate the team's creativity originating from the freedom of thought. Some of the interviewees assert that AM requires a PD process of higher flexibility, focusing more on early-stage discussions instead of the review gates. The complexity of formalizing the PD process is amplified by the simultaneous need to develop the technology itself and, therefore, to cope with the uncertainty related to materials selection, design and qualification of the printing processes, and certification of the components' design and function capabilities. To assist the standardization of the PD procedure, the Company works on diverse instruments turning AM into a "steady state" process; one example is the software to continuously monitor the build job using the neural networks in automated inspection of each layer.

Taken in total, this case study demonstrates how AM introduction triggers the adjustment of an entire product creation process, demanding, at the same time, an organizational change within the Company. It affects the whole process chain, from design to manufacturing and service, including materials and software development. However, to make a comprehensive assessment of the overall impact, this work sees the need to enable a compound quantitative analysis of the identified transformation points' cumulative influence. Furthermore, the total effect will vary depending on the scenario and context of the application. Therefore, such a solution must be configurable and allow its use in various circumstances. This need is addressed with the development of the custom analytical instruments described in Chapter 4.

But before introducing the proposed solutions, it is essential to draw the particular implications for the ICM process based on the described study. The following subsection specifies the influence of the product creation process transformation on the ICM practice.

3.3 The impact of AM-triggered transformations on the ICM process

Comprehensive use of AM throughout the whole product lifecycle changes the architecture of the creation process in many ways. Hence, each alteration in the PD and manufacturing system echoes in the ECM, MCM, and, eventually, ICM procedures. The vast design space provides an enormous scope of the decision alternatives. However, to effectively exploit it, the change management team must be prepared to navigate the previously uncharted fields. It also needs methods for concurrent investigation of multiple alternatives to grasp the potential advantage of using a set-based design-like approach. Further, with more digitalized prototyping techniques that rely on 3D printing, the design-test loops mainly shrink, although, can sometimes appear slower due to the low TRL of a chosen printing process.

Therefore, to grow an AM capability, the company needs to adopt the ICM approach to ensure a crucial interconnection between engineering and manufacturing. Thus, the necessity of an ICM concept – that this work discusses initially in a general context – is further emphasized by the need to efficiently operate in the AM paradigm. The ICM process shown in Figure 3.6, in turn, is expected to experience a similar transformation when operated through AM. Since, in many ways, AM promises to enhance the PD operations, its adoption is expected to bring several positive alterations in ICM in a like manner.

At the intersection of change implementation in engineering and manufacturing, AM can bring a more gradual transition compared to the conventional setting. As discussed in section 3.1, the change implementation team faces a critical quality gate that requires freezing the design decisions before investing in the detailed development and execution of the manufacturing change. With AM, it seems to be less demanding concerning the product design changes or tooling procurement for the manufacturing process. However, the need for qualification and certification of the product and process might counterbalance or exceed the benefit of AM's digitalized agility. Also, the ICM team needs to be equipped to analyze the tradeoffs in planning a manufacturing change: for example, one decision can minimize the print preparation effort but increase the amount of work in post-processing. A quantitative evaluation of the cost and lead time implications is necessary to select a better option.

Moreover, we see that the roles distribution can be different in the AM context. Hence, the system of the main stakeholders, such as shown in Figure 3.4, can deviate as well. Accurate evaluation of the techno-economic impact caused by such organizational and process changes requires a numerical assessment. Therefore, before introducing the new roles into the product creation system – e.g., the AM technologist role – it is necessary to quantitatively study the implications to the change lead time and budget expenditures. Such an analysis requires a configurable analytical tool, which will allow to variate the process and organization architectures and numerically compare their techno-economic performance. Extending this further, the AM's impact on the team's overall interaction degree needs a similar measurable analysis.

Finally, when formalizing a standard PD or ICM procedure for a given context, the company again needs to conduct a quantitative evaluation of the alternatives. The potential instrument for that should provide the capability of laying out different process architectures, such as the detailed ICM process in Figure 3.6, and accurately evaluate it with respect to, e.g., the change lead time and cost.

All the alterations mentioned above primarily transform the dynamics of the process. Specifically, they define the durations of the activities, as well as the probabilities and impacts of the rework iterations. These changes, in turn, characterize the process time- and cost-performance. Seeing the AM's potential to accelerate the product development process significantly, this work recognizes a need to provide the means, which will allow identifying the speed of the operations that will be optimal for a given project in terms of the lead time and expenditures. Chapter 4 proposes the method to address these challenges.

Chapter 4

Model-based analytical framework: evaluating the cost and times of the integrated change management process

An integrated analysis of engineering and manufacturing changes requires the methods to provide a necessary granularity and study an entire space of process design alternatives. As in many other engineering disciplines, researchers have used various modeling techniques to scrutinize the product development (PD) systems' architectures subject to their time efficiency and financial performance. Though this work did not find any prior work on modeling ECM or MCM processes in particular, there is a great body of knowledge devoted to generic PD processes. Thus, in section 4.1, this work first reviews the existing PD modeling methods and then implements an ICM-specific solution based on them. Further, to take another step towards an integrated analysis of PD and manufacturing systems, this chapter looks into the state-of-the-art quantitative evaluation of production operations in general and additive manufacturing (AM) specifically. It identifies the gap in applying advanced modeling techniques – that rely on simulation-based modeling – for accurate cost- and time-based assessment of the AM-enabled systems. Addressing this gap, section 4.2 introduces a self-developed modeling framework based on the use of commercial software. Finally, section 4.3 demonstrates the method to realize integrated modeling of PD and manufacturing activities by combining the presented techniques into a single framework. However, before going into the field-specific discussions on analytical methods, this section first makes a broader review of the cost- and time-based systems' evaluation.

A systemic analysis of the product creation process can come from consideration of its four primary competitive characteristics: quality, time, cost, and flexibility. Through them, the systems can be juxtaposed across a variety of alternatives (Gutowski, 2002). In this work, two characteristics – time and cost – are considered foundational, assuming that the others can be derived from them. At the manufacturing system level, the time-based estimations rely on the process-level estimations. The latter can be done through fully analytical definitions of involved physical phenomena or process simulation relying on analytical formulations of more granular sub-processes. This work adheres to simulation-based methods, given their superiority in representing the complexity of production systems (Pehrsson, Ng and Stockton, 2013). The time-based evaluation of the PD processes is more complicated as it shall account for the in-process generation of novelty and creativity, which induce the uncertainty in estimation (Kline, 1985; Browning, Fricke and Negele, 2006). Section 4.1 will discuss the specific methods of PD effort estimation.

Product development expenses are usually defined from the effort, wage rates, and computational requirements for engineering activities. The estimation of expenditures related to manufacturing aspects, which consume most resources (see Figure 2.1), is trickier. It must accurately account for various cost categories, or prisms of project financial evaluation, which can be attributed as recurring and non-recurring, fixed and variable, or direct and indirect. The non-recurring category includes the expenditures on activities that happen only once during the lifecycle, whereas recurring embodies those that reoccur for each unit of output, e.g., materials procurement. Variable and fixed cost types designate spending that correspondingly can and cannot change production cost when the output rate varies. The direct costs can be broken down and attributed to a specific item or cause, but indirect costs cannot be assigned to a particular object or action of creation and are, therefore, considered overhead. All these cost types will be considered at different project stages – from product R&D to its retirement and disposal – and across all involved activities (Curran, Raghunathan and Price, 2004). Thus, it is a challenge to evaluate the total cost precisely.

Balancing between the accuracy and the ease of applicability, researchers came up with different cost estimation methods. Distilling the list of "major software cost estimation techniques" presented by Boehm (1984), Curran, Raghunathan, and Price (2004) summarize the methods under three categories: analogous, parametric, and bottom-up. In an analogous approach, the cost of a target product is adjusted relative to a similar product manufactured before engaging an expert judgment. The parametric method uses the numerical drivers that scale the product cost based on a correlation found from the historical data. The bottom-up approach would use a detailed work breakdown structure (WBS) and aggregate the expenditures in distinct tasks into a total cost. Additionally, the authors acknowledge the emergence of more advanced estimation approaches utilizing feature-based modeling, data mining, neural networks, or fuzzy logic techniques. The authors then reclassify all the methods under two major categories being compilational and relational costing.

A similar set of methods has been reviewed by Brinke (2002) and then summarized into three basic approaches: generative-based, variant-based, and hybrid cost estimation (a combination of the first two methods). The author attributes the techniques relying on the data of similar past projects as variant-based, i.e., analogous in the terminology of Boehm (1984) and Curran, Raghunathan, and Price (2004), and those that compose the cost from its constituents as the generative methods, i.e., bottom-up. Brinke also compares them around the cost estimation paradox introduced by Bode (1998): cost estimation gets more precise with an increase of knowledge about the product, however, defining more product attributes decreases the ability to make changes influencing the cost. The author asserts that with the variant-based methods, there is more information available at earlier PD stages, implying the possibility of more accurate estimations with such approaches at the same level of cost commitment.

Later, Park and Simpson (2005) have complemented this terminology considering the simulation-based methods. The authors have attributed this new category to the techniques relying on simulation tools that accurately estimate the factory operation costs. Being detailed in the representation of the production process, they can precisely account for the direct costs, such as material, labor, and processing time spent on a given unit, and the indirect costs, such as work-in-progress inventory and internal logistics.

Moreover, given the variation in accuracy and efforts required for data collection and processing with different cost estimation methods, Park and Simpson (2005) suggest applying them correspondingly along the project maturation stages. Accounting for the differing sets of cost contributors and levels of data availability, such a hybrid method would use variant- and generative-based methods during the early development stage, which has a low portion of indirect costs, and a simulation-based costing at the stage with high data availability and need for proper consideration of the process stochasticity. With a similar perception, Niazi *et al.* (2006) present a decision-support workflow for selecting an efficient cost assessment methodology and suggest another comprehensive classification for various estimation techniques.

Section 4.2 will detail the discussion on manufacturing cost and time evaluation and present a chosen method along with its implementation for the additive manufacturing context. But before that, section 4.1 reviews the effort estimation techniques and introduces a developed approach for quantitative assessment of the PD operations.

4.1 An analytical framework for the evaluation of product development operations

The planning of product development operations is complicated by the creativity and uncertainty involved in the design process. In the attempts to quantify the temporal and financial expenditures, researchers have developed various estimation methods. In the early study, Bashir (2000) addresses the problem of engineering project overruns by reviewing and applying different models for design effort estimation. The author compares two categories of methods based on the use of expert judgment (EJ) and the metrics, respectively, and concludes that the latter minimizes a subjective estimate and has a potential for more precise effort evaluation. Recognizing a need for a more accurate assessment of the product complexity, the author proposes to evaluate it through the functional decomposition of the potential product. Based on that, the author then examines three specific techniques: the parametric models, the general regression neural network (GRNN) models, and the analogy-based model. The author concludes that all of them have performed with a comparable estimation accuracy exceeding the methods previously applied in the studied companies. However, each of them had a flaw in a certain aspect. The parametric models based on traditional regression analysis demonstrate the utility in effort estimation and suitability for sensitivity analysis, as shown by Bashir and Thomson (2004) on the hydroelectric generators example. However, they are contingent upon the selection of the regression function, and a poorly chosen form of a mathematical relationship will lead to inaccurate estimations. The GRNN-based method, according to Bashir (2000), depends on the data-based probability density function instead of a presumed function yet still requires the historical relationship patterns between effort and other independent design variables, the effort drivers. The analogy-based method is applicable to the projects on new product type but requires a higher experience of the estimator, i.e., the expert or user, howbeit still less than pure EJ.

On the other end, Rush and Roy (2001) develop the discussion on the importance of EJ in the cost estimation techniques. The authors note that even though computerized cost models reduce the need in the EJ, they cannot fully replace them being dependent on the input of users' expertise and judgment. Therefore, the authors pursue improving the EJ method by formalizing a reasoning process behind the analogy-based costing. Further, in contrast to Bashir's reliance on the metrics approach, Roy *et al.* (2001) highlight the importance of making a distinction between the "thinking" and "non-thinking" time during the design process and also propose a technique for more accurate estimation of the former. The authors suggest paying more attention to the qualitative cost drivers, such as the PD team's experience or perceived complexity of the 3D model development, which, as a result, affects the thinking time. They have provided the methodology for formulation of the Cost Estimating Relationships (CERs), which aims to synthesize the data from the past projects on the same product type into quantitative and qualitative cost drivers, and then account for them in an integrated manner. As recommended, the qualitative CERs can be derived from the questionnaires filled in by the team leader and the designers.

Later, Johnson (2004) adapts the approach of Roy *et al.* (2001) for collecting the EJ data, which is then used to design a process-based cost model assessing the development and manufacturing operations. Using it, the author searches for a cost-effective design balance between consolidating the parts within a product into one component, and thus reducing the overall assembly effort, or breaking them up into a larger group of parts, adding more flexibility in sharing them across product variants. The model includes a range of the cost drivers, such as the part commonality among the product variants, and falls into the category of the metric-based methods discussed above by Bashir (2000). Using the model, the author identifies the major drivers of the efforts, and hence costs, in engineering and manufacturing, as well as quantifies the fractions of different cost categories. Based on that, the study has found the decisions on parts consolidation and sharing, which led to the savings in PD cycle time and cost.

Although the methods reviewed and elaborated by Bashir (2000), Roy *et al.* (2001), Rush and Roy (2001), and Johnson (2004) have demonstrated the practical applicability, their product- and organization-centric perspective seem to be insufficient for a comprehensive study of the PD operations.

Since they do not explore product creation from the process domain angle and mostly view the project as the set of contributing factors, they do not take account of the factors' variable influence during the project's evolvement. In other words, these methods, in essence, view the PD process as a *"static"* phenomenon, not attributing its "*dynamic"* properties. They also overlook the added value or detriment that these factors can make if perceived as the interconnected elements of the process, which basically is a system with many relationships and interfaces (Browning, Fricke and Negele, 2006). In practice, given that the PD process is a complex and changeable network of interrelated activities, it can follow various scenarios even if the input values on quantitative and qualitative cost drivers discussed above are the same. The implementation of the project largely depends on the execution path chosen by the PD team. A selected architecture of the PD process, i.e., the set of constituent steps and interrelations among them, influences the project performance enormously (Browning and Eppinger, 2002). The team can also prefer different alternatives in terms of the frequency and scope of the in-process reviews and iterations characterizing the project and accordingly choose between, for example, the staged and spiral process options (Unger and Eppinger, 2009).

Considering the above, this work argues that in evaluating and planning the upcoming project, it is critical to not only accurately estimate the qualitative and quantitative effort and cost drivers but also to find the most promising execution scenario in terms of project lead time and resources expenditure. Speaking in a more practical language, the realization of such a hybrid approach – coupling the static and dynamic views of the process – necessitates both a metrics-based model analysis, which would synthesize the design complexity, and the simulation-based analysis to study the alternative execution scenarios of the PD operations. First of all, such comprehensive predictive analysis of the PD project demands a reliable systematic way of its representation.

Since the 1950s, the academic and industrial communities have developed a great number of approaches to organize, model, and analyze the dynamic nature of PD activities. They target various issues associated with process planning, coordination, and resources optimal utilization (Hamraz, Caldwell and Clarkson, 2013; Wynn and Clarkson, 2018). Browning (2009) gives a summary of 25 common process model views, each of which has proven its practical applicability. Generally, the developed techniques are either graph- or matrix-based (Jun and Suh, 2008). Browning and Ramasesh (2007) note that many models focus on the process actions, i.e., steps, but do not consider the interactions, i.e., the flow of deliverables between them. They also note that not all of them are applicable for project-level improvements, as some models are used for local optimization between two activities.

Among this variety of techniques, the *Design Structure Matrix* (DSM) provides one of the most compact structuring methods that emphasize potential iterations and rework loops and facilitate the analysis of the project duration and cost drivers (Browning, 2009). In general, DSM is applicable not only to processes representation but to any compound system. According to Eppinger and Browning (2012), DSM is an N by N square matrix that maps the interactions among the set of N system elements. Figure 4.1 demonstrates the way to interpret the binary DSM by showing an equivalent representation of an abstract system of seven elements (a-g) in the digraph form: the row marks serve as the inputs (IR, i.e., input in rows) to the element, whereas the column contains the outputs. However, there is also an opposite convention when the element's inputs are in its columns (IC) and the outputs are in its rows; therefore, one should define which convention to use before starting the DSM analysis. In this work, we follow the IR convention.

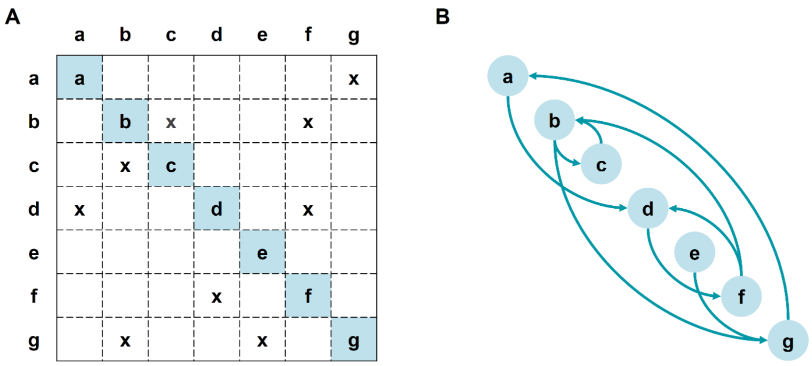

Figure 4.1. **(a)** binary DSM, **(b)** equivalent digraph form; adapted from (Eppinger and Browning, 2012).

In engineering systems design, the DSM's primary applications lie in modeling the product, process, and organization involved in the PD project, connecting either subsystems (components), or activities, or people correspondingly, as shown in Figure 4.2. Additionally, the DSMs can be assembled into a larger matrix that would reflect the interdomain connections, as shown in Figure 4.2d; such a view is called the *Multidomain Matrix* (MDM). This matrix of matrices shows a holistic view of intra-domain and inter-domain relations by including the domain-specific DSMs and the *Domain Mapping Matrices* (DMMs). The latter aids in clarifying the relationships between the domains, e.g., showing which people execute which process activities, and verifying the constituent elements.

The application of DSM to practical industrial problems on process modeling has started in the early 1990s. In most cases, the objectives include representation of the current process architecture (the sequence of the constituent elements, i.e., activities), its analysis towards activities interconnection (e.g., if they are sequential or parallel), highlighting iteration and rework, and definition of a more efficient process architecture. It has been shown that it is necessary to not only eliminate the non-value-adding activities (following the lean principles) but also to study the interactions between the activities since bad inputs to value-adding activities can lead to undesirable results. In this regard, the DSM-based approach has the strength that stems from its ability to capture the whole picture. In the case of process modeling, it shows a full set of the inputs and outputs within the system, whereas the other modeling methods, e.g., flowcharts and Gantt charts, in most cases represent only the minimal set of interconnections (Eppinger and Browning, 2012).

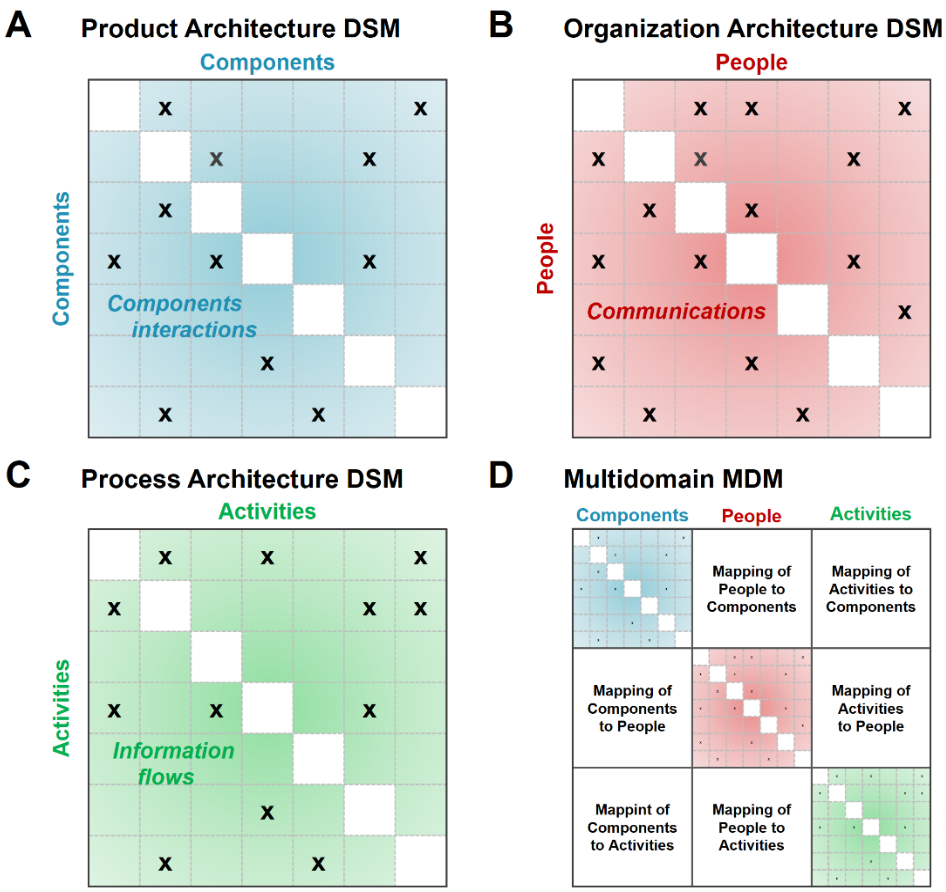

Figure 4.2. Primary DSM applications; adapted from (Eppinger and Browning, 2012).

Further, combining the DSM-based process model and a specific simulation technique can produce the tool for analysis and benchmarking of PD process dynamics. This is necessary to enable rigorous process study: for example, when searching for the shortest process time, the simulation tool might demonstrate that the DSM-driven minimization of the iterations number through process partitioning and tearing does not guarantee the optimal result (Abdelsalam and Bao, 2006). In the early work, Osborne (1993) has compared eleven modeling approaches (other than DSM) that differ in the input form and applications. As none of the reviewed methods was sufficient to characterize an iterative nature of the PDP, the author has incorporated the selected methods into a custom "iterative process modeling" approach based on DSM. Later, Browning, Fricke, and Negele (2006) overviewed a wider spectrum of 18 modeling techniques applied to the PD process and compared the involved assumptions and the viewpoints on the process. They have come to a similar conclusion on the variation of competitive advantages across the methods, thus stating the need for a generalized PD modeling framework which would systematically encapsulate many views and the major process objects (e.g., activities, deliverables, and organizational units) into one rich model. These conclusions imply that when approaching PDP modeling, one should consider combining the strengths of different techniques to achieve the most realistic representation of the process.

In general, the simulation logic varies, and depending on the process type, i.e., the presence of the serial, parallel, or coupled activities in it, the method can be or not appropriate for describing the particular business case (Karniel and Reich, 2009). The lesser the number of the modeling constraints in the approach, the more potential scenarios it can investigate; therefore, such comprehensive methods as the one demonstrated by Cho and Eppinger (2005) seem to be more suitable to describe complex process options.

In application to the analysis of ICM, and specifically to ECM, the closest work is related to the development of the change propagation tools that investigate the influence of factors in the product, process (change), or organization (people) domains. For example, Pasqual and de Weck (2012) propose a multilayer network model, Ouertani and Gzara (2008) the DEPNET solution, and Ahmad, Wynn, and Clarkson (2013) the ISF framework. Yet, it seems that not much has been done in modeling the ECM reference process for cost- and time-based assessment, especially when iterations and rework are considered. This work believes that applying the DSM-based simulations – such as those discussed in (Karniel and Reich, 2009) – can help to benchmark and improve the ICM workflow structures and implementation scenarios. To address the gap, building on the prior work in this area, the following subsections introduce the part of the analytical framework that has been implemented for simulation-based analysis of the ICM reference process.

4.1.1 The structure of the ICM process

The first step to make is to define the reference process that will become the backbone of the process model. Based on the detailed description of the ICM process in section 3.1, we derive a higher-level reference process for using it in the model. This section stays at a high level of operations and does not elaborate on the lower-level operations discussed in section 3.1 or the literature, such as (VDA 4965, 2010b), to keep a reader focused on the proposed method. Nevertheless, the architecture of the proposed approach, i.e., an input-to-output data pipeline, can simulate more detailed workflows. The solution is designed to depict as many steps as required and, therefore, is applicable for describing the interconnections within the ICM reference process illustrated in section 3.1. Thus, in explaining the modeling method and demonstrating the use case (Chapter 5), this work generalizes an integrated reference process to a generic ECM process shown in Figure 4.3. However, its implementation would require an analytical framework capturing a broader scope than just for ECM simulation, i.e., providing the necessary granularity for the analysis of manufacturing activities. This concern is addressed in sections 4.2-4.3.

A selected process defines the sequence of steps, i.e., activities, for the object to go through during the change execution, which are given on the DSM's main diagonal, as shown in Figure 4.3. It captures the high-level activities and decisions between the creation of the change request and its implementation in manufacturing. The workflow progresses ahead until it is necessary to iterate; in Figure 4.3, the feedback iterations are shown in the super diagonal cells, whereas the feedforward iterations are given in the sub diagonal space. In this process, the first iteration can happen after the risk assessment step: if the previously identified solution is inappropriate, the process returns to the previous stage to identify other solutions (Clarkson and Eckert, 2005). The second source of iteration is at the decision stage, i.e., where the change committee can request additional risk analysis before approving or disapproving the change (Clarkson and Eckert, 2005). Another potential source of iteration is lying between the engineering and manufacturing implementation activities: here, it can occur because of the unsatisfactory manufacturability analysis results or difficulties to support the change by the suppliers, logistics department, shop floor operators, or other involved stakeholders (Shakirov *et al.*, 2019). We omit the change review step, assuming that the change implementation steps capture it. Also, appendix A4 provides a detailed version of the DSM that is based on the ICM process described in section 3.1 and the MCM model architecture presented by Koch (2017).

	1	2	3	4	5	6
1	1. Change request creation					
2		2. Identify the potential solutions	*Iteration 3→2*		*Iteration 5→2*	*Iteration 6→2*
3		*Feedforward rework 2→3*	3. Risk/impact assessment	*Iteration 4→3*		
4			*Feedforward rework 3→4*	4. Decision on a change by the committee		
5				*Feedforward rework 4→5*	5. Implement the change in engineering	*Iteration 6→5*
6					*Feedforward rework 5→6*	6. Implement the change in manufacturing

Figure 4.3. The generic Integrated Change Management reference process.

4.1.2 Model implementation

To analyze such an iterative process, we integrate the DSM representation with the discrete-event simulation (DES) tool in the vein of the approach presented by Browning and Eppinger (2002) and then enhanced by Cho and Eppinger (2005). The major PD modeling rules followed in this work are below:

1. The duration of each activity follows the triangular probability distribution for its comprehensibility to the project planner (Williams, 1992). Therefore, we use three input parameters for each activity *i*: minimum duration $MinD_i$, most likely duration MLD_i, and maximum duration $MaxD_i$, as shown in Figure 4.4.

2. In general, the complexity of the process, including concurrency, is synthesized in the indicators presented in sections 4.1.3.1-4.1.3.3. Concurrent engineering is therefore embedded in the model. However, at the ECM process level, which is embedded within each major design process, it is not required to consider the overlapped individual tasks, as presented in Figure 4.4. Therefore, in the simulation, it is required to have final output information from the upstream activity before the downstream can begin.

3. Depending on the probabilistic outcome of the executed activity, the process may loop into the sequential iteration with preceding operations until reaching the probabilistic state that allows it to proceed. To account for such rework, we assign the respective rework probability RP(i,j,r) ($0 \le$ RP(i,j,r) ≤ 1) after executing the step j, i.e., giving a certain chance for proceeding or returning to the previous step i for its r'th iteration, as demonstrated by (Cho and Eppinger, 2005). If the need for rework occurs after step j, its duration is calculated based on the nominal duration of activity i and the rework impact factor RI(i,j), representing the fraction of work to be repeated ($0 \le$ RI(i,j) ≤ 1). The possible causes for rework are failure to meet the specified requirement or change of the output data from the preceding reworked activities. Using the RP(i,j,r) and RI(i,j) values as the framework inputs, we define the process DSMs for probabilities and impacts correspondingly, as shown in Figure 4.4.

4. Aiming at the accurate estimation of the rework amount for a particular subsystem, we are using the initial learning curve factor LF_i^{init} ($0 \le LF_i^{init} \le 1$) to evaluate the rework duration of step i similarly to (Cho and Eppinger, 2005). We also define the task *i'*th minimum rework amount as an input, which corresponds to the LF_i^{max} ($0 \le LF_i^{max} \le 1$) fraction of the original duration as shown in Figure 4.4. Here, we assume that there is a database of past ECs on the same subsystem type by the same design team necessary to define the historical indicators such as those described in section 4.1.3.

Having the process defined with the input parameters shown in Figure 4.4, we can create the discrete-event simulation (DES) model. In this work, we employ Microsoft® Excel® for matrices construction and Tecnomatix Plant Simulation™ 14.2 software (*Plant Simulation and Throughput Optimization | Siemens Digital Industries Software*, 2021) for process modeling and scenarios investigation. At the initialization of DES, the model imports an input data from the spreadsheet file (i.e., the values of duration, rework probability and impact, learning curve factors, organizational units amount for all components underground the change) and replicates the DSM-based structure with corresponding process parameters following the prescribed modeling rules, as shown in the modeling framework in Figure 4.5.

Process steps	Durations input			Learning curve
1. Change request creation	$MinD_1$	MLD_1	$MaxD_1$	
2. Identify the potential solutions	$MinD_2$	MLD_2	$MaxD_2$	
3. Risk/impact assessment	$MinD_3$	MLD_3	$MaxD_3$	LF_i^{init}
4. Decision on a change	$MinD_4$	MLD_4	$MaxD_4$	LF_i^{max}
5. Implement the change in engineering	$MinD_5$	MLD_5	$MaxD_5$	
6. Implement the change in manufacturing	$MinD_6$	MLD_6	$MaxD_6$	

Rework probabilities input

#	1	2	3	4	5	6
1	1					
2		2	$RP(2,3,r)$		$RP(2,5,r)$	$RP(2,6,r)$
3		$RP(3,2,r)$	3	$RP(3,4,r)$		
4			$RP(4,3,r)$	4		
5				$RP(5,4,r)$	5	$RP(5,6,r)$
6					$RP(6,5,r)$	6

Rework impacts input

#	1	2	3	4	5	6
1	1					
2		2	$RI(2,3)$		$RI(2,5)$	$RI(2,6)$
3		$RI(3,2)$	3	$RI(3,4)$		
4			$RI(4,3)$	4		
5				$RI(5,4)$	5	$RI(5,6)$
6					$RI(6,5)$	6

Figure 4.4. DES model input parameters.

The DES model is set up to execute this step automatically using the built-in object-oriented programming language. By this, the framework enables flexibility in scenarios investigation and supports the integration of decisions made in the organizational (i.e., available human resources at each step) and process domains. During the simulation, the model keeps track of each subsystem undergoing the change, assigns the respective probabilistic values, counts the iterations, and calculates the durations.

Once the simulation is complete, the model outputs the report with data on overall project duration, i.e., change lead time, and iteration statistics. Further, the model runs a series of observations and documents the variability of the process; such capability is necessary to juxtapose different change scenarios or process structures in terms of the mean lead time and standard deviation, as shown in the model use-case given in section 5.4. With this information, the project manager can search for the balance between the process reliability, i.e., total duration variability, and robustness, i.e., duration's sensitivity to rework probability (Yassine, Whitney and Zambito, 2001). However, the precision of such a model-based assessment is highly contingent upon the set of input parameters, which values depend on a range of factors given below.

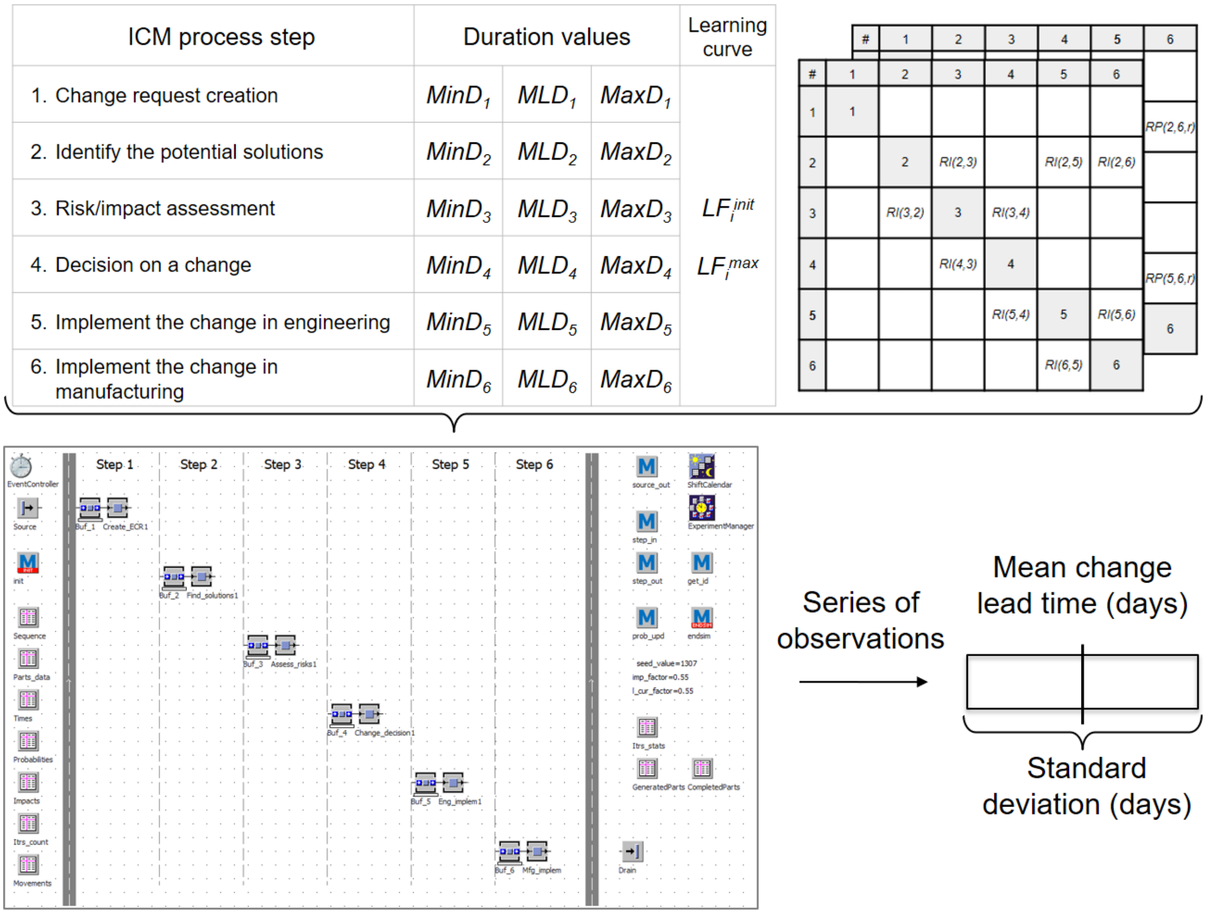

Figure 4.5. Overview of the proposed modeling framework; the discrete-event simulation model. The description of the major model objects will be given in Figure 4.10.

1. The durations $MinD_i$, MLD_i, and $MaxD_i$ of the activity i are assumed to reflect the specific amount of effort necessary to perform it, i.e., they do not include the time periods when the activity has been on hold or waiting for the organizational resource. They are highly dependent on the difficulty to meet the technical specification such as geometrical dimensions and tolerances and component's structural complexity (i.e., how far can the change propagate). Other contributing factors might be the product functional complexity, PD team expertise, requirements on the technical documentation, and involvement of the design partners (Bashir and Thomson, 2004).

2. The rework-associated parameters $RP(i,j,r)$ and $RI(i,j)$ might have a variety of uncertainty-related factors influencing engineering design. This includes the epistemic uncertainty caused by the lack of knowledge about the system of operations and the causal relationships in it, i.e., ambiguity, as well as the aleatory uncertainty brought by the natural variation in values of the system variables (Wynn, Grebici and Clarkson, 2011; Yang *et al.*, 2014). According to Wynn, Grebici, and Clarkson (2011), these factors can originate at five *uncertainty levels* – imprecision, inconsistency, inaccuracy, indecision, and instability – which capture the multiplicity of circumstances for rework. They include:

- multiple descriptions of the design parameters causing their inconsistency;
- modeling simplifications causing inaccuracy in design and analysis tasks;
- the complex organization of activities leading to a *"limited overview of information flows and dependencies in the process"* (Wynn, Grebici and Clarkson, 2011);
- imprecise assumptions on parameters' values when working with cyclic dependencies;
- lack of trust in the available information.

3. The learning curve parameters LF_i^{init} and LF_i^{max} reflect the engineer's learning process during the iterations of activity i. The typical factors influencing their values are the prior experience that the worker can acquire from the past work on similar activities (Nembhard and Uzumeri, 2000) and the task complexity, which determines the time necessary to comprehend the problem (Shafqat *et al.*, 2019).

Altogether, these factors express the difficulty to accurately quantify the model parameters due to the complexity and creativity involved in PD operations. Therefore, there is a need to find an approach to the justified assessment of the parameters' values. For this, a concept of an approach addressing the problem will be discussed below; its central assumption is the availability of a database of past change projects involving the necessary component types. Section 4.1.3 delineates the idea of using historical data to reduce the uncertainty in assigning the model input values.

4.1.3 An approach to refine the modeling parameters

The utility of the proposed modeling approach highly depends on how accurate is an estimate of the simulation parameters. Therefore, the difficulty to quantitatively assess them passes a significant amount of uncertainty in the simulation results. Specifically, the numerical input values for the activities' durations, likelihood and impact of rework, and the learning curve definition are of great importance (Clarkson, Simons and Eckert, 2004). In the work of Browning and Eppinger (2002), Cho and Eppinger (2005), Abdelsalam and Bao (2006), these values have been presented as part of the project-specific dataset. Wynn, Grebici, and Clarkson (2011) defined these values through qualitative explanations (based on the five uncertainty levels mentioned above) and algebraic expressions, which an expert constructs for a given context following the particular set of questions. In both approaches, we see an outweighing reliance on subjective estimations, which induce uncertainty. This work proposes to reduce the latter by complementing the presented model- and simulation-based method, i.e., a dynamic view on the process, with a static view on it through the PD effort estimation techniques discussed by Bashir (2000), Roy *et al.* (2001), Rush and Roy (2001), Johnson (2004), and at the beginning of section 4.1 (p. 72), such as the metrics method.

Therefore, we propose to enhance the experience-based judgment with the project-specific analytical indicators derived from historical data. Since the latter is based on real facts, its application should reduce the uncertainty and empower the experts with better evaluations. Naturally, the quality of estimations will improve with the amount of past information available from the current project and past projects of a similar nature. According to the literature, within different companies, we can consider the following change information being available (Giffin *et al.*, 2009; Wasmer, Staub and Vroom, 2011; Comuzzi and Parhizkar, 2017):

- ECM descriptive information (e.g., Change Number, project ID).
- Product-related information (e.g., parts, assemblies).
- People-related information (e.g., people, roles).
- Time-related information (e.g., timestamps, dates).

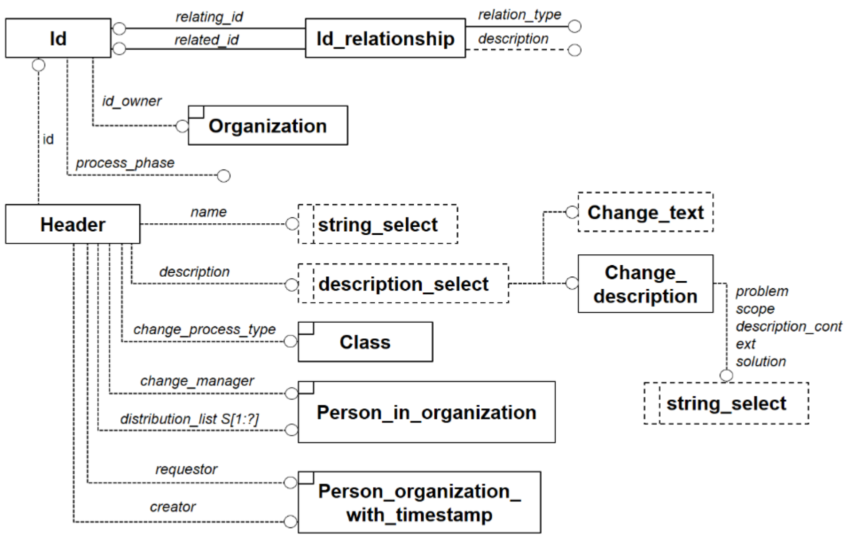

Figure 4.6. Excerpt of the Header data model, adapted from (VDA 4965, 2010c).

To achieve a finer estimation of the modeling parameters related to activity durations and iterations, this work proposes to utilize the retrospective indicators that quantitatively characterize the past change processes. Essentially, we aim to synthesize the complexity of the design process – including its concurrency, interdisciplinarity, and varying learning capability – and provide cost-effective practical applicability. Kattner, Shakirov, and Lindemann (2019) use graph analysis to calculate effort metrics for components of a technical system using historical data. By defining a meta-model for the change structure and leveraging change information about parts, people, and change IDs, network analysis – adapted from (Biedermann, 2015) – allows deriving metrics for effort drivers for the technical system's components. Based on this, the following five retrospective indicators, which Kattner, Hu, and Lindemann (2019) discuss in more details, seem to be relevant for the definition of change effort:

- *Indicator for the number of changes to a component:* In the graph-based analysis of ECs, the node degree of a component with edges to change nodes represents the number of changes to the component.
- *Indicator for the number of people involved in the change of a selected component:* Within a graph-based change network, the mean node degree of all change nodes for a selected component based on edgetypes "people" represents the number of people involved in a change to that component.
- *Indicator for the iteration behavior of changes to a component:* Since there is a high chance of iteration within the EC process, the indicator shows the reappearance of people in the same change process for a selected component.
- *Indicator for the change propagation behavior of a component:* Within the network analysis, the propagation can be derived by the edges connecting components in the same change ID. Thus, the number of involved (propagated) components represents the propagation indicator.
- *Indicator for the collaboration resistance for changes to a component:* Since the interconnectivity of changes can be extremely high, the complexity of change handling can influence people's collaboration due to uncertain responsibility or distributed cooperation. Thus, the higher the distribution within a company of people involved in a change, the more difficult it gets to collaborate and make decisions.

Since the change details that the company collects and stores may vary from one firm to another, this work assumes the setting with limited data availability. As such, we suppose that there is access to information on the number of changes each part type has gone through in the past, the number of parts types involved in the same change request, and the change propagation pattern. Also, there is access to the number of documented people who worked on each change request, which reflects a full-time equivalent (FTE) effort of a given EC, and to the number of unique people involved in the EC, i.e., a headcount in the EC-specific team. This reasoning is based on the availability of such data in the ECR data model presented in the VDA documentation and in other related literature (Giffin *et al.*, 2009; VDA 4965, 2010b; Wasmer, Staub and Vroom, 2011; Comuzzi and Parhizkar, 2017). Furthermore, if such data is documented during the execution of the ECM process, then it should be available in the historical database of the past projects; this assumption is based on the need to comply with standards such as ISO9001 forcing companies to ensure change traceability (Clarkson and Eckert, 2005). A method to calculate the model input parameters relying on the EC indicators is given below.

4.1.3.1 *Estimating the activities durations $MinD_i$, MLD_i, and $MaxD_i$*

Since in many cases there is no trace of the actual activities' durations, i.e., without the idle or waiting times, these values need to be estimated; therefore, the modeling precision depends on the correctness of durations prediction. To improve it, in this example, we use the selected indicators in an estimation model (1) that scales PD effort with the values of those indicators. By doing this, we expect to mitigate the subjectivity of the expert prognoses by combining them with the project-specific effort drivers.

$$\boldsymbol{E_{comp} = E_{est} \cdot NPR_{comp} \cdot NPE_{comp} \cdot NCR_{comp}}, \tag{1}$$

Where:

- E_{comp} – is an estimated design effort in hours to be spent on the component;
- E_{est} – is an expert estimation that characterizes an effort necessary for the most time-demanding component in the system (i.e., for the component with the maximum values of NPR, NPE, and NCR);
- NPR – is the normalized change propagation factor reflecting the product complexity and showing the networking degree of the part under change (normalized from 0.1 to 1);
- NPE – is the normalized factor reflecting the headcount of people involved in the same change request (normalized from 0.1 to 1);
- NCR – is the normalized collaboration resistance factor, which reflects the difficulty of decision-making due to the distribution of involved people within a company (normalized from 0.1 to 1). Importantly, the chosen set of indicators complements the modeling method with the consideration of concurrent activities performed by different team members.

By providing an estimate of the minimum, most likely, and maximum effort values expected by the expert using E_{est}, applying equation (1), we can evaluate the values of $MinD_{cur}$, MLD_{cur}, and $MaxD_{cur}$ of the current EC. Out of the derived $MinD_{cur}$, MLD_{cur}, and $MaxD_{cur}$ values of the EC process, the experts can make better estimations of the activities' durations by distributing the process duration according to their judgment. However, if the company tracks specific effort values for each activity of the past projects, i.e., there is access to $MinD_i$, MLD_i, and $MaxD_i$ values in the past projects, we suggest using those to define the case-specific distribution law.

4.1.3.2 *Estimating the rework probabilities RP(i,j,r) and impacts RI(i,j)*

The accuracy of estimating the rework probabilities *RP(i,j,r)* contributes to the precision with which the model represents the iterations happening along the ECM process. We presume that the historical data on the overall EC FTE accounting for repetitive work on the same EC by the same person and EC-specific headcount can reflect the rework intensity for an EC component and thus help experts improve the predictions. Specifically, based on such data and using equation (2) below, we can estimate the average people reappearance factor $\overline{RF_{comp}}$ for an EC component using the past *N* number of EC cases that involve it. We can then derive a normalized (from 0.1 to 1) people reappearance factor *NRF* for an EC component, as shown in (3).

$$\overline{\boldsymbol{RF_{comp}}} = \frac{1}{N}\sum_{k=1}^{N}\frac{PFTE_k}{PHC_k}, \tag{2}$$

Where:

- $PFTE_k$ - is the number of people involved in the past EC *k* reflecting its overall FTE;
- PHC_k – is the headcount of people involved in the past EC *k*;
- *N* – is the number of the cases involving the subsystem.

$$\boldsymbol{NRF_{comp}} = \frac{\overline{RF_{comp}} - RF_{comp}^{min}}{RF_{comp}^{max} - RF_{comp}^{min}} \cdot \mathbf{0.9} + \mathbf{0.1}, \tag{3}$$

Where:

- RF_{comp}^{max} – is the maximum people reappearance factor in the system;
- RF_{comp}^{min} – is the minimum people reappearance factor in the system.

Having NRF_{comp} factor calculated, we can tune the original probability estimations $RP(i,j,r)_o$ of the process – that are evaluated through expert guesses for a component with the highest RF_{comp} – to represent the EC of a current component using (4).

$$\boldsymbol{RP(i,j,r)_{comp}} = \boldsymbol{RP(i,j,r)_o} \cdot \boldsymbol{NRF_{comp}} \tag{4}$$

The rework impact factors *RI(i,j)* are challenging to derive using past data as it would require information on all past activities' specific duration along with detailed EC narrative documentation. Given the unavailability of any reference to collecting such data, in this work, we assume that the *RI(i,j)* values are derived solely from the expert estimations.

4.1.3.3 Estimating the learning curve factors LF_i^{init} and LF_i^{max}

Here we assume that the initial and maximum learning curve factors (LF_i^{init} and LF_i^{max}) of an upcoming EC are dependent on how many times a given component has gone through the ECs in the past. This data can be represented by the component's normalized changes count factor NCC_{comp} (normalized from 0.1 to 1) described in (5), as it implicitly reflects the cumulative experience of re-engineering the component by the company. Hence, if there were many ECM cases involving the given component, the learning factors of the current EC, which are calculated with (6) and (7), would be higher, i.e., enabling the iteration with shorter durations. Therefore, the original learning factors LF_o^{init} and LF_o^{max} - which serve as the datum points to compute the component-specific factors - should equal those of the component with the highest change count.

$$NCC_{comp} = \frac{CC_{comp} - CC_{min}}{CC_{max} - CC_{min}} \cdot 0.9 + 0.1, \tag{5}$$

Where:

- CC_{comp} – is the number of past ECs of the component;
- CC_{max} – is the maximum number of past ECs per component;
- CC_{min} – is the minimum number of past ECs per component.

$$LF_i^{init} = LF_o^{init} \cdot NCC_{comp} \tag{6}$$

$$LF_i^{max} = LF_o^{max} \cdot NCC_{comp} \tag{7}$$

In this work, we propose to use the learning model as proposed by (Cho and Eppinger, 2005), in which the durations of the tasks are defined through the linear relationship with the iterations count *r*, limited with the LF_i^{max} factor. Equation (8) shows how it affects the duration D_i^r of activity *i*:

$$D_i^r = D_i^o \cdot RI(i,j) \cdot max(1 - r \cdot LF_i^{init}, 1 - LF_i^{max}), \tag{8}$$

Where:

- D_i^r – is the duration of activity *i* at the *r*'th repetition ($r \geq 1$);
- D_i^o – is the original duration of activity *i* that is evaluated following section 4.1.3.1.

Taken in total, the above provides an organized simulation-based approach of using historical data in the evaluation of the upcoming ECM projects. It aims to improve the effort planning accuracy by assessing the values of tasks' duration, rework probabilities, and learning curve factors when simulating the subsystem-specific reference process. Such a method has a substantial potential for improving the expert estimates and thus the overall prediction capability at the project planning stage. However, the rather simplified scaling rules represented in equations (1)-(8) shown here can be revised and complemented with more strict company-specific assumptions, along with more thorough estimation techniques as in (Bashir, 2000). For example, characterization of the learning curve parameters could account for the design team experience and its variable impact on different process tasks.

4.1.4 Model output

As shown with Figure 4.5, the major output of the model is an estimation of the EC lead time. Specifically, the framework provides the change board with quantitative evaluations on EC lead time mean and standard deviation, thus indicating the reliability and robustness of the particular change management process. Also, the framework has been prescribed to count the number of iterations of different steps and calculate the PD labor expenditures as a product of an overall effort (hours) and the engineer's hourly rate[33] (USD/hour). Altogether, this information provides better guidance in project planning and is expected to improve the scheduling of the EC projects.

Among the main applications of the model, this work sees the comparison of different change scenarios, e.g., selection of the component to trigger the change, and the study of different process architectures, e.g., selection of the constituent steps and proneness to iterations among them, subject to required effort. Both types of analysis will be discussed in more detail in Chapter 5, devoted to the framework use case.

However, the application of the approach described so far can be insufficient for a comprehensive analysis of the project planning tradeoffs related to its duration and cost. This is related to the implementation of changes in manufacturing and quantitative evaluation of the induced costs. The EC planning decisions – especially those related to steps iterations and rework – will define the expenditures on product manufacturing and production system reorganization. This means that a more dynamic and iterative process might require many iterations connected to product manufacturing and demand a larger budget and project duration shares spent on production. Therefore, the corresponding time and cost expenditures need to be accurately estimated before the final decision on process architecture is made.

Furthermore, the shop floor decisions can also have a substantial impact on the project performance. On the example of the ICM reference process shown in Figure 4.3, we can imagine that the procurement and manufacturing planning decisions will determine the cost and duration of step 6, "Implement the change in manufacturing." Hence, they must be the primary considerations in overall project planning. All related implications of change implementation – both in terms of scheduling the EC process and manufacturing resources allocation – need to be quantified at that stage beforehand. This emphasizes the significance of integrating the numerical model-based analysis of engineering and manufacturing decisions and providing the corresponding instruments for the comprehensive analysis, as discussed in section 2.1.4.

To address this, the next section demonstrates the method of evaluating the time and cost expenditures spent in production on the example of the additive manufacturing-based facility. Then, combining the approaches presented in sections 4.1 and 4.2, this work addresses the discussed above need for integrated analysis in section 4.3.

[33] This work assumes that an engineer's salary does not depend on the type of product to work on.

4.2 An analytical framework for the techno-economic evaluation of manufacturing operations

As discussed at the beginning of Chapter 4, the difficulty of manufacturing operations' evaluation is associated with the variety of cost categories. It is especially problematic to accurately assign the expenditures that cannot be directly attributed to a specific unit or action of production. In other words, a chosen cost estimation method shall precisely assess and allocate among the output units not only the recurring, variable, and direct costs but also the non-recurring, fixed, and indirect ones.

In the current practice, an Activity-Based Costing (ABC) method allows measuring expenditures with high accuracy. In the terminology used by Curran, Raghunathan, and Price (2004), it is a bottom-up or compilational approach, which was introduced and popularized in the mid-'80s by Cooper and Kaplan (1988b). ABC can be referred to as the generative method in Brinke's categorization (Brinke, 2002), and under the classification of Niazi *et al.* (2006), it falls under the category of quantitative analytical techniques. Its precision comes from a high level of granularity: in comparing the costs of two components produced at the same facility, it would be necessary to allocate the expenditures at the activity level instead of the product level (Cooper and Kaplan, 1991). In the latter approach, previous methods have distributed the costs according to the parts production volumes and experts guesses on their cost contributions. Such procedure has been acceptable in the preceding manufacturing era, where the direct labor and material costs almost fully made up the total cost. With the introduction of new production technologies and automation, it has become necessary to pay more attention to the overhead cost categories, such as equipment maintenance and logistics (Cooper and Kaplan, 1988a). Barber, Dewhurst, and Pritchard (2006) provide a clear illustration of the difference between ABC and conventional methods.

Cooper and Kaplan (1991) reasonably argue that it is necessary to distinguish the factory operating expenses at four levels: unit, batch, product-sustaining, and facility-sustaining levels. The resources consumed at one level (e.g., the batch level expenses for setup) do not vary because of another level (e.g., the material and labor at the unit level), and therefore also cannot be controlled by it. This critical distinction allows to granularize on various cost contributing activities accurately and then analyze their linkages to the revenue generation and resources consumption. As a result, ABC quantitatively exposes a business performance based on the influence of the current product line, customer base, or employed distribution channels. With such analytics, a company is better equipped to plan the changes driving profits increase.

As shows this four-level categorization of the factory operations, ABC strongly emphasizes a proper identification of the cost drivers determining a quantitative scaling of a given cost category. Spedding and Sun (1999) suggest considering three types of cost drivers based on transaction, duration, and intensity. The *transaction* drivers are those that do not depend on the activity's duration, i.e., consuming the same quantity of resources at each activity's occurrence (Kaplan and Anderson, 2003). The *duration* drivers scale with the time taken by the activity (e.g., printing time). And the *intensity* drivers consider the varying amount of resources taken during the activity (e.g., the inert gas consumption during printing). ABC's initial concept did not include the duration drivers, what caused the impediments associated with data collection, storage, maintenance, and processing; because of that, at the outset, ABC had reduced practical applicability and accuracy (Kaplan and Anderson, 2003). The consideration of duration has transformed ABC into time-driven ABC, which addresses the stated limitations by paying significant attention to the effort-based cost drivers.

The addition of intensity drivers is also critical for accurate cost estimation with ABC. In (Barber, Dewhurst and Pritchard, 2006), the authors stress the importance of accounting for a variable resources' impact by proposing a resource-based costing method, in which they also highlight the possibility of change in resources costs throughout the year. Park and Simpson (2005) provide an overview of the cost drivers building on four levels of the product breakdown structure. Inspired by it, this work suggests following the matrix of cost drivers proposed in Figure 4.7: by identifying the drivers of different types at four activity levels, one can ensure comprehensiveness in cost factors definition while building a manufacturing cost model.

Activity level / Driver type	*Unit*	*Batch*	*Product*	*Facility*
Transaction				
Duration				
Intensity				

Figure 4.7. The matrix of manufacturing cost drivers.

To advance further from the outdated accounting principles and enhance an ABC-based practice, researchers and industry professionals have elaborated the methods relying on simulation. In a seminal panel devoted to manufacturing costs estimation, Zuk, Kleindorfer, Nordgren, Moore, and Phillips have drawn multiple arguments on the need to combine the strengths of simulation-based modeling – and Discrete-Event Simulation (DES) in particular – and ABC (Zuk *et al.*, 1990). Two of the most compelling reasons to employ DES are its ability to provide a complete summary of production activity and support ABC's granularity. It is because the events of DES and the activities of ABC represent an absolute match and thus can attribute to the same process segments (Spedding and Sun, 1999).

Additionally, due to the timing mechanism of the DES approach and the same data type as in ABC, this combination enables the combined performance and economic analysis (Zuk *et al.*, 1990). This way, we can access a comprehensive techno-economic study of the production systems, including the time-based metrics critical for AM industrialization. The panelists also acknowledge the superiority of an approach based on ABC and DES in justifying the adoption or rejection of the technological innovation at the shop floor through an accurate techno-economic assessment of an upcoming change. It is also related to a specific advantage of simulation in that it can be "fast-forwarded into the future to obtain realistic projections of further running costs and expenditure" (Spedding and Sun, 1999).

Pehrsson, Ng, and Stockton (2013) argue that simulation is the only way to deal with production systems' complexity, and it also helps to avoid productivity losses when investing in manufacturing technology. In this context, DES surpasses the analytical models as the latter cannot handle such complexity because of modeling or solution reasons (Evans and Haddock, 1992; Labitzke, Spengler and Volling, 2009). Furthermore, with DES, it is possible to output the cost ranges instead of the single point estimates by accounting for intrinsic process variations. It gives better support in decision-making and shows the cost drivers' interconnections (Beck and Nowak, 2000). Spedding and Sun (1999) discuss the steps necessary to implement ABC in simulation.

Later, Labitzke, Spengler, and Volling (2009) introduce a fair distinction between the costing methods relying on simulation. If the cost estimation happens after the simulation run using the data produced by the latter, such an approach shall be considered as "*simulation-based costing*." It is the case for one of the earliest examples of using simulation in costing presented by Takakuwa (1997). If the costs are calculated throughout the simulation, i.e., the chosen estimation technique is integrated into the same model, then it is a "*cost simulation*" approach. Spedding and Sun (1999) provide one of the earliest instances of this. The method selection would depend on the capability to account for the costs during the simulation run. For example, Moore discusses the difficulty in allocating the "leftover" costs that are not associated with one single activity, i.e., overheads, and therefore names them as "unallocatable" (Zuk *et al.*, 1990). The author notes that idle machines, idle labor, or unused facility space entail such costs, and it is easier to account for them after the simulation than along it. Still, there remains a challenge of allocating the costs of any system element staying idle. Cooper and Kaplan (1988b) suggest that an accounting system shall treat such costs separately from the product costs, e.g., as "a cost of the period."

Building on the two options of DES and ABC integration, this work suggests a hybrid approach that combines cost simulation and simulation-based costing ideas. Following it, the system will define the "allocatable" costs during the simulation run and the "unallocatable" costs after it. Such perspective has been implemented in this work and described later in this section with respect to idle costs evaluation.

Researchers have presented various applications of cost estimation based on ABC and DES within the last three decades. Takakuwa (1997) has investigated the operations of an automated, flexible manufacturing system (FMS) for the cost contributions of different system elements and juxtaposed seven scheduling rules in terms of resulting products' costs. Spedding and Sun (1999) have evaluated the efficiency of the quality control system in Printed Circuit Boards (PCB) manufacturing. Beck and

Nowak (2000) elaborated an example of a pen factory described by Cooper and Kaplan (1988b). Özbayrak, Akgün, and Türker (2004) have also studied an automated FMS and compared different push and pull scheduling strategies. Barber, Dewhurst, and Pritchard (2006) revised the business processes at the small and medium-sized enterprise (SME) subject to downsizing. Comelli, Féniès, and Tchernev (2008) compared two supply chain management strategies on a tire manufacturer case. Labitzke, Spengler, and Volling (2009) have analyzed four modification alternatives for a steel production inventory concerning its utilization, throughput time, and costs, though using Riebel's Generic Direct Costing instead of ABC. Marsh *et al.* (2010) assessed the costs and operations time for different assembly sequences. Calvi *et al.* (2019) evaluated seven alternative configurations of a system conducting re-manufacturing operations for electronic devices in terms of their throughput, costs, and utilization. Murphy *et al.* (2020) apply the method on a modified P&Q problem from the literature.

Nevertheless, despite the high accuracy of the simulation-enabled costing tools, the tendency of applying them is low (Labitzke, Spengler and Volling, 2009). Presumably, it is because of a greater work effort associated with model development and data collection than in other analytical methods. Especially, this work sees the gap in employing cost simulation in the AM context. As we can see from a recent literature review on AM costing methods, such analysis has not been used extensively for an AM-enabled environment (Kadir, Yusof and Wahab, 2020).

For example, Mounsey, Hon, and Sutcliffe (2016) use simulation-based costing for AM but consider only the printing stage. Stittgen and Schleifenbaum (2020a, 2020b) use the operating curves theory to investigate the throughput times and productivity of an AM-enabled manufacturing system but do not study the economic aspects and omit the build preparation and post-processing stages. Moreover, given that a current TRL of metal AM is insufficient for its reliable use, such an exhaustive study shall incorporate the analysis of quality costs, i.e., consider the expenditures associated with the defects and inspection operations, as discussed in (Schmid and Levy, 2012; Hajalfadul and Baumers, 2020).

To make a comprehensive study on the AM's cost-effective use cases, which will consider the influence of various production planning decisions, it is essential to examine a complete workflow's techno-economic performance, i.e., from build preparation to product quality control. Otherwise, a company might be at risk of experiencing losses triggered by the technology introduction (Pehrsson, Ng and Stockton, 2013). The following subsections describe how this work employs a method based on ABC and DES to enable a techno-economic analysis of a full AM workflow considering the production planning decision.

4.2.1 A modeling scope to address

To understand the economic implications of deploying AM at different production scales, in different application contexts, and with variable levels of overall machine performance and efficiency, we need to account for the related recurring and non-recurring production costs. As shown in Figure 4.8, this work reviews the production process that is based on the laser powder bed fusion (LPBF) technology. We propose to define the total production cost by tracking the expenditures in four major categories: labor, capital, consumables, and materials. All categories will be considered at each of the workflow stages discussed in section 2.2.3: build preparation, printing, post-processing, and quality control (QC). To provide the necessary granularity of the cost model, we represent each stage with a corresponding sequence of steps contributing to those cost categories. As shown with the printing stage example, these steps would include the operations related to machine setup (e.g., build plate installation, powder refill, machine warm-up, and inerting), processing (i.e., printing), machine recovery (e.g., machine cool down, powder removal), and maintenance (both regular preventive maintenance and service of failures).

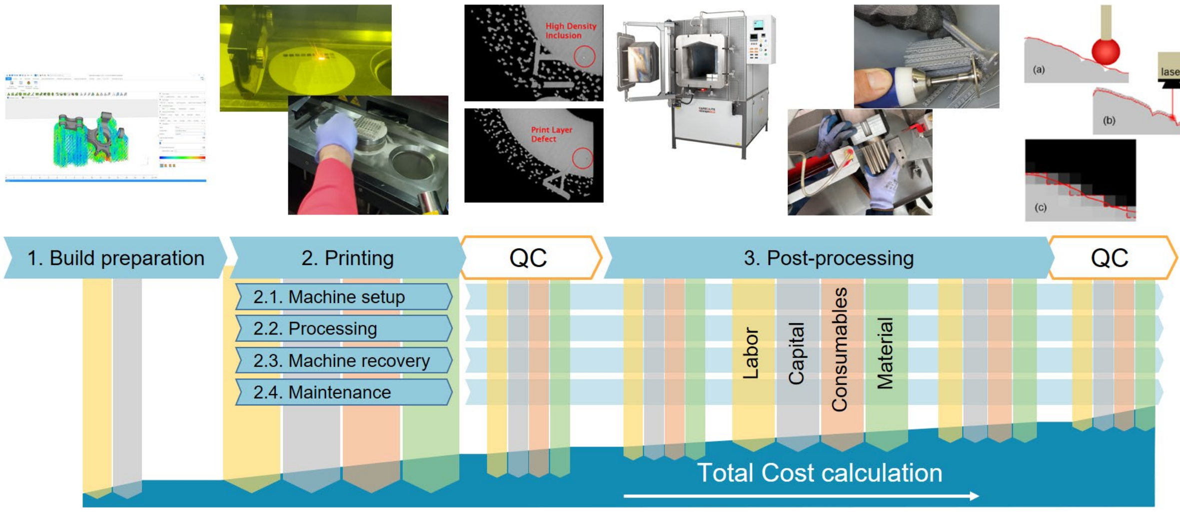

Figure 4.8. Accounting the costs of LPBF-based manufacturing workflow[34].

4.2.2 Implementing Activity-Based Costing through simulation-based modeling

Management literature suggests numerous methods to account for and assign manufacturing costs (see the beginning of Chapter 4). For the model proposed in this work, a time-driven Activity-Based Costing (ABC) method is utilized for its intuitive and configurable mathematics and its ability to be granularized to accurately account for a wide range of manufacturing steps (Niazi *et al.*, 2006). Described succinctly, an ABC model defines discrete production activities as granular as an operator conducting specific machine maintenance or as general as an entire print or build cycle. Each activity is assigned a cost and a time, and these values are divisible by the number of units worked on to produce

[34] Figures sources (left to right): tctmagazine.com, qualitymag.com, azom.com, swissplasticsplatform.com, Leach *et al.* (2019).

a cost per part which can be linked intrinsically to the constituent production tasks from which the final component cost is derived.

Consequently, the output fidelity of an ABC model directly depends on the accuracy of time and cost estimates for each of the constituent activities accounted for within the model. To provide a simulation approach with a resolution commensurate to that of ABC, this research employs the discrete event simulation (DES) technique[35]. For this, the AM production workflow is segregated into a necessary set of states, where the transition from one state to another occurs instantaneously upon the conclusion of previous events. For example, consider the processing unit, an AM machine, which after completing a "cooldown" event, switches into a "waiting" state, i.e., holds until the operator would execute a "coming over" event and turn the machine into the "service" state. By using a high degree of detail in characterizing events, the DES method produces a granular view into production activities.

With an outlook into future applications of the framework, the stated method was implemented by developing separate factory element libraries for major operations capture in simulation, i.e., for build preparation, printing, and accompanying post-processing operations. Therefore, in future this approach can be adapted to the related AM processes, such as binder jetting, material extrusion, directed energy deposition, etc.

4.2.3 Overview of the implemented solution

Figure 4.9 provides an overview of the manufacturing modeling framework and shows its major elements. The methods and tables of [1] govern the system behavior and determine the framework's architecture in terms of overall data flow and processing. It is the brain of the framework, which: reads and processes all case-specific input data; configures the manufacturing system [3] accordingly; governs the factory scheduling decisions, such as the sequencing of orders, parts batching, and tasks assignment to processing units (Harjunkoski *et al.*, 2014); defines the operational logic for every object of the system; accounts for the costs of the process; and calculates the simulation output parameters [4]. The framework input includes the manufacturing system parameters defined in [2] and other case-specific data defined with the Excel® file. The latter is expected to contain the information on parts to produce and the machines used in the process. As shown in [5], the framework uses the built-in "Experiment Manager" instrument to conduct the necessary simulation studies based on the selected input variables. Additionally, Figure 4.10 provides the keys to reading the major objects of Figure 4.9, relying on the software Help documentation.

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[35] Realized in Tecnomatix Plant Simulation™ 14.2 (*Plant Simulation and Throughput Optimization | Siemens Digital Industries Software*, 2021).

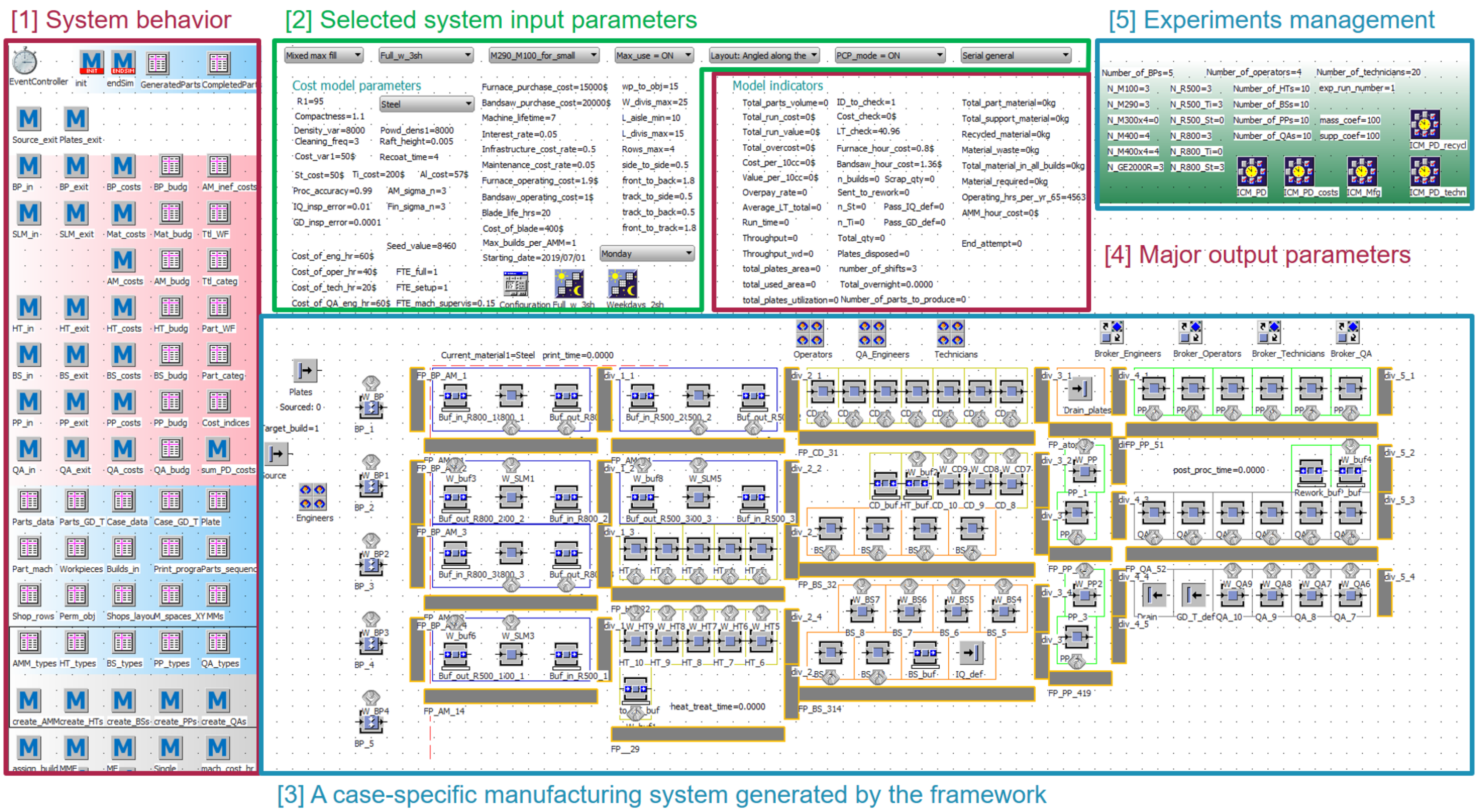


Figure 4.9. Overview of the manufacturing modeling framework. The major in-model abbreviations are: *init* for initialization; *BP* for build preparation; *SLM* for selective laser melting; *HT* for heat treatment; *CD* for cooldown; *BS* for build plate separation; *PP* for post-processing and manual supports removal in particular; *QA* for quality control and assurance; *FP* for foot path; *AMM* for additive manufacturing machine.

EventController	An object that coordinates and synchronizes the different events taking place during a simulation run.	WorkerPool	An object that represents the lounge or the staff room of the factory.	Dialog	An object to define a specific user interface necessary.
Source	An object that generates the workpieces. It has a capacity of one and no processing time.	Broker	An object that connects the services offered and services required by distributing the workforce.	ExperimentManager	An object that supports the user in executing simulation studies.
AssemblyStation	An object that adds mounting parts to a main part.	Workplace	An object that representes the actual place at the station where the worker performs the job.	Enter your text here	A drop-down list confining the number of alternative values for a specific modeling parameter.
Buffer	An object used to imitate storage and warehouse of the parts and workpieces	ShiftCalendar	An object governing the working schedule of the factory.	Variable=0	A global variable that other objects and methods can access during a simulation run.
Station	An object that has a single station for processing a part.	FootPath	An object representing the path on which the worker walks from the Workerpool to the Workplace	Frame	An object used for grouping objects and to build hierarchically structured models.
Drain	An object that removes the parts and workpieces from the plant after they have been processed.	Method	An object used to program controls that other objects rely on. The programming language is SimTalk.	DataTable	A list with two or more columns containing the data in a specified format (e.g., Integer, String, Table).

Figure 4.10. The description of the major objects used in the modeling framework.

The simplified logic of the production process and corresponding information flow are illustrated in Figure 4.11. When the simulation commences, the model reads the input data, deletes the system elements from the previous simulation, and creates the new ones for the current case or observation. After that, the model assigns the first batch of parts to be prepared in a single build according to one of three prescribed batching strategies. This batch gets to the build preparation step, where an engineer works on creating an STL (Standard Tessellation Language) file for it; this STL file serves as a source of detailed instructions for the AM machine to follow in printing this particular build. When this operation is completed, the build is sent to the printer, which will create a physical embodiment of a given digital representation. After that, the build goes through heat treatment for stress relief and consequent build plate removal. Out of the plate removal station, the parts are separately routed to the respective entrance buffers of the post-processing stations. The finished parts move to quality control (QC), where the engineers examine the parts for material defects and GD&T. The parts that do not have the defects move to the inventory. If QC finds a defect that can be eliminated at the post-processing step, then the engineer sends it there; if the defect is critical and the part cannot be restored, the system assigns a new part to be printed by updating the corresponding manufacturing program tables. When all of the parts get to the inventory, the model ends the simulation and calculates the necessary output parameters related to the system's cost and time performance. Then, they can be accessed in the simulation report or in the exported Excel® file. Below, this chapter details the general logic, rules, and associated assumptions – both qualitative and quantitative – taken at each step of the simulation process.

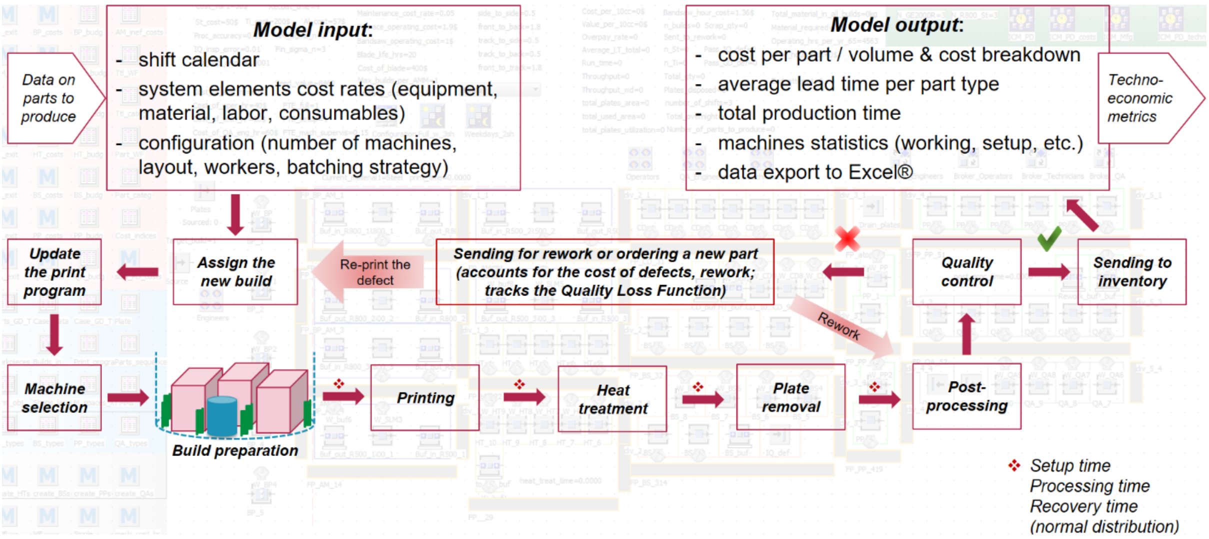


Figure 4.11. Process flow of the manufacturing modeling framework.

4.2.3.1 Model input

The model's input is defined at two levels: internally in the model and externally with the Excel® files. The internal input defines the manufacturing system's configuration and the generic parameters that usually do not change from case to case compared to the parts' geometric characteristics or machines' specifications. The major configuration parameters are the following:

- *Number of machines of each type and material* – when necessary, a user defines the numbers of machines of certain type and dedicated to the specific material inside the model (to reduce the simulation time when running the series of experiments by skipping longer functions of reading from Excel®).
- *Batching strategy* – a predefined algorithm of parts allocation into the same build (a user selects one of three predefined strategies).
- *Number of employees* – reflects the staffing level in the system, i.e., how many engineers, operators, and technicians are available in the system (a user inputs a positive integer value).
- *Shift mode* – defines the operation patterns for the employees; a user selects one of two predefined shift modes: *the 24/7* pattern for three shifts operating seven days per week (168 hours total, the exact number of employees' groups is not specified) or *the weekdays* pattern with two shifts operating five days per week (80 working hours total).
- *Layout parameters* – characteristics of the shop floor layout specifying the limits of corresponding length and width dimensions.

- *Use of a plate utilization increase mode* – an ON/OFF selection of the mode to print the builds in the build chambers of the machines with smallest suitable dimensions (following the assumption that larger machines have a higher hourly cost rate).

Other generic internal parameters of the manufacturing model include:

- *Compactness* – a factor that defines the distance between the parts in the build; specifically, it multiplies the length and width of the part bounding box and thus secures a space around the part (e.g., compactness of 1.1 results in the distance equal to 10% of its width and length).
- *Hourly cost rates for the employees* –hourly salaries for the engineer, technician, operator, and QC engineer.
- *Track to machine side distance* – a standard distance between the footpath and the machine defined by the local layout planning standards.
- *Interest rate* – a cost of capital representing the opportunity cost of spending the liquid capital instead of investing it on a fixed interest rate.
- *Materials cost rates* – the cost of Steel, Titanium, or Aluminum allows per kg.
- *Preventive maintenance period* – a default number of days between the preventive maintenance operations.

The external input to the model characterizes the parts to be produced and the machines to be used in the process. As shown in Table 4.1, for each of *N* part types, the input includes the ID number, data on its dimensions, volume of supports necessary in the LPBF process (as a fraction of the part mass), post-processing complexity (as a multiplying factor on the default post-processing productivity measured in grams per hour), and data on days given to produce the specified volume. Additionally, the user can define the quality-related requirements on the part's material properties (e.g., porosity) and on geometrical dimensioning and tolerancing (GD&T); this input would guide the rate of defects during production, associated rework, and resulting costs spent on quality control (with higher values for high-precision parts).

The input on machines involved in the process needs to include the information on their dimensions, performance characteristics, corresponding consumption rates, cost rates, expected lifetime, and quantity in the system. The major parameters are listed in Table 4.2. Having all the input data defined, the user can proceed with simulation initiation.

Table 4.1. Input data on the parts to produce.

Parameter	Description	Unit
Part ID	A unique identifier for a particular part type	-
Production Volume	A number of parts of a given type to produce	pieces
Material	A material of the part	(type)
Length, Width, Height	Dimensions of the part's bounding box	m
Part Volume	The volume of the part	m^3
Supports Fraction	The ratio of the supports mass to the part mass	-
Post-processing Complexity Factor	An integer factor (between 1 and 4) multiplying the default supports removal rate of 30 cm^3/hr	-
Given Days	A number of days given to produce the necessary number of parts	days
Internal Quality (IQ) Parameter to Track	Specification of the IQ parameter that needs to be tracked within the production process	(type)
Lower Specified Limit of The IQ Parameter	A lower limit value for the tracked IQ parameter	-
Geometrical Dimensioning and Tolerancing (GD&T) Parameter to Track	Specification of the GD&T parameter that needs to be tracked within the production process	(type)
Lower Specified Limit of the GD&T Parameter	A lower limit value for the tracked GD&T parameter	-
Upper Specified Limit of the GD&T Parameter	An upper limit value for the tracked GD&T parameter	-

4.2.3.2 Model initialization

With simulation initialization, the model runs the *init* method, which first updates the tables with the corresponding input data and creates the objects for each part type to be produced. Importantly, it defines which machines would be suitable for which parts in terms of build chamber size and material. Further, the method sorts the list of parts based on the Given Days parameter and a rough estimate on the overall production time (in days) necessary for a given part type; the lesser the difference between the Given Days value and production time, the earlier in the sequence the part would be. After that, the method creates the manufacturing system's layout and assigns the first build to be prepared and produced. Those two functions are described in detail in the following subsections.

Table 4.2 Input data on machines to be used.

Parameter	Description	Unit
Number of Machines	A number of machines of this type in the system	-
Plate Dimensions	Length, Width (or Diameter), Height	m
Height of the Build Chamber	Max vertical dimension of the build chamber	m
Effective Area of the Plate	An estimate for an average usable area of the plate	m^2
Powder Waste Fraction	Define the fraction of powder volume that is unrecyclable	-
Volume of The Powder Refilling Hopper	Tracks the need to refill the hopper	m^3
Machine Purchase Cost	Machine sale price	USD
Machine Lifetime	A life expectancy of a machine	years
Infrastructure Cost Rate (as Fraction of The Machine Purchase Cost)	Defines the cost of infrastructure necessary to use the machine	-
Maintenance Cost Rate (as Fraction of the Machine Purchase Cost)	Defines annual expenses on machine maintenance	-
In-Process Consumption Rate of the Inert Gas	A rate of gas (e.g., Argon) inflow into the build chamber during the printing process	L/min
Cost of Inert Gas	Cost of inert gas per liter	USD/L
Build Plate Cost	Cost of one machine-specific build plate	USD
Build Plate Refurbishment Capacity	A number of times the build plate can be refurbished (e.g., with milling)	-
Cost Per Refurbishment	Cost of refurbishment operations	USD
Warm-Up Time	An amount of time necessary for a machine to start printing after the process initiation	hours
Build Rate	A machine's rate of material deposition	cc/hr
Cool-Down Time	An amount of time necessary for a machine to cool-down the build chamber	hours
Uptime Rate	A percentage of time during which machine is working in an uninterrupted manner	-
Average Power Consumption	A power consumption rate	W
Layer Thickness	A thickness of one powder layer to be melted by the laser	µm
Machine Dimensions	Length, Width, Height of the machine	m
Space Requirements	Length, Width, Height of the space necessary for machine operation	m

4.2.3.3 Layout generation

The task of the layout generation method is to generate and allocate the machines, buffers, and storage elements – one-by-one, along the aisles – in compliance with the space limitations defined by the internal input parameters. In doing so, the model first removes the objects of the previous simulation, then creates the machine objects, adjusting the dimensions of their 3D representations according to the specifications listed in Table 4.2, and assigns its attributes given in Table 4.2 with their respective values defined in the Excel® file. The method starts with positioning the build preparation (BP) stations that resemble the engineers' workstations for STL files creation. Then, the AM machines and their buffers are placed next to the BPs, being limited by the maximum length and width of the division, as shown in Figure 4.12. With the same restrictions, the method keeps creating and arranging the ovens, bandsaw machines, post-processing and quality control stations, as well as the system buffers until all the system objects are allocated.

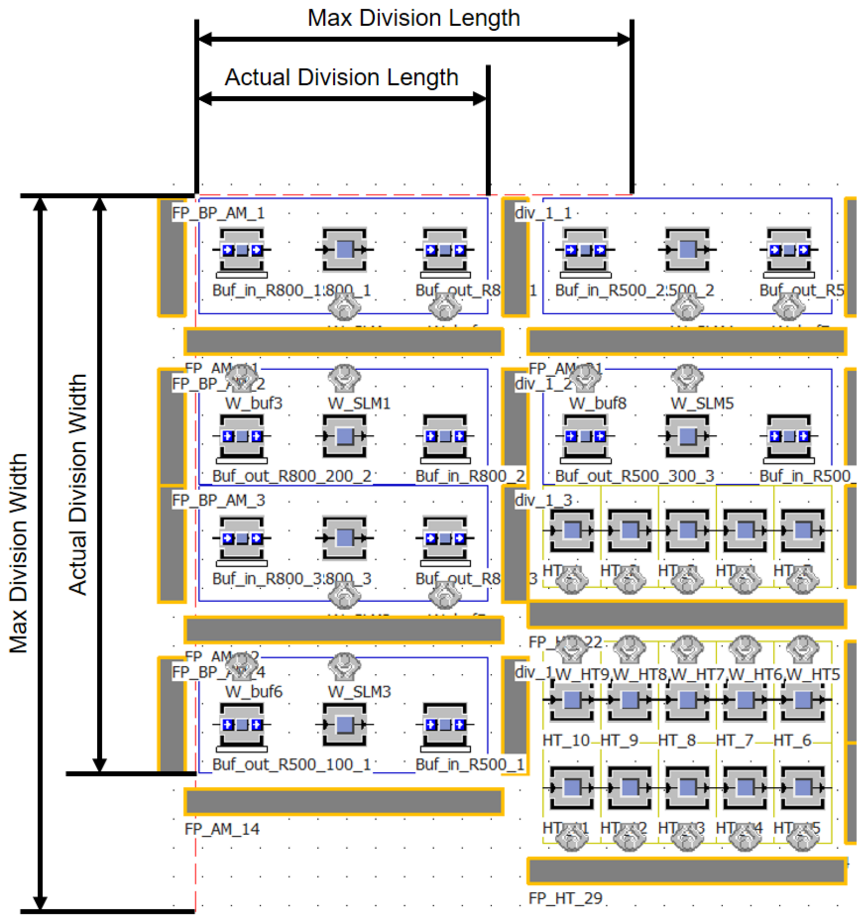


Figure 4.12. The maximum and actual length and width of one layout division (the example division demonstrated on the left includes the AM machines and the buffers for builds entrance and exit).

4.2.3.4 The procedure of assigning the build

After positioning the manufacturing system elements, the model can proceed with the assignment of the first build. The first run of the *assign_build* method happens during initialization; if there are still parts to be produced after that build is assigned, it is called again to process the next batch of parts at the moment when the object of the previous build's last part is created. The method starts with restricting the list of machines to those suitable for processing the first part type in the sequence (i.e., if the part can fit into the build chamber and if the machine is set up for a necessary material).

When the vector of suitable machines is prepared, the method calls a *find_machine* method that selects the most appropriate machine from the list in terms of three criteria (in the selection order): (a) the number of builds already assigned to the machine; (b) an estimated time until becoming unoccupied; (c) the build chamber size of the machine. Based on a first criterion (a), the method selects the machines with the same minimum number of builds assigned. It is also connected with the positive integer input parameter called *Max_builds_per_AMM*, limiting the number of builds that can be queued to the same AM machine. If the minimum value of *builds_assigned* is equal to the limitation, then the system waits until one of the machines finishes the build. In general, if such limitation parameter is too large, the system might assign too many builds and create a long queue for the part that is ordered later for the rework. This can be a critical case for the parts with the highest priority in the sequence, as it can drastically increase the prognosed time of completion for this part type. Therefore, it is assumed that the model should have a minimum value of the *Max_builds_per_AMM* parameter providing a necessary machines utilization performance and yielding maximum responsiveness of the manufacturing system to changes in the orders. Hence, we can regard it as one of the tuning elements of the system's agility.

The second criterion (b) chooses the machines with the least expected time until completion of the already assigned builds. In case there are several machines with the same time value (e.g., in the very beginning of the simulation where all machines are vacant and those values are equal to zero to all of them), the method comes to the third selection criteria. In (c), the algorithm selects a machine with the largest possible build volume, i.e., a multiplication of the plate area on the maximum build height. This rule follows the assumption stating that the machines with larger build volumes have higher hourly cost rates; therefore, the system is configured to first of all increase the actual uptime rate for those machines. If there are still several machines in the list, the method will choose the last one.

Once the machine is identified, the *assign_build* method proceeds with batching the parts, i.e., formulating the list of parts that will compose the build. There are three prescribed batching strategies that are illustrated in Figure 4.13: *mixed max fill, single*, and *max fill*. *Mixed max fill* aims to minimize the per-build costs associated with setting up the printers by assigning the maximum number of parts per build job, which may include components with different geometries and bounding box dimensions. *Single* attempts to minimize the overall lead time (i.e., the time required for one part to complete all production stages, including non-working hours) for each part by assigning a single part to each build job. The *max fill* strategy, which attempts to both reduce the lead time and costs of auxiliary steps – such as machines warm-up, build plate installation, and cooldown – batches only parts of the same ID within each build. As with the *mixed max fill* strategy, the *max fill* batching approach allocates the maximum number of components per build job as can be produced according to the cross-sectional area of the part's bounding box and the build area of the equipment utilized.

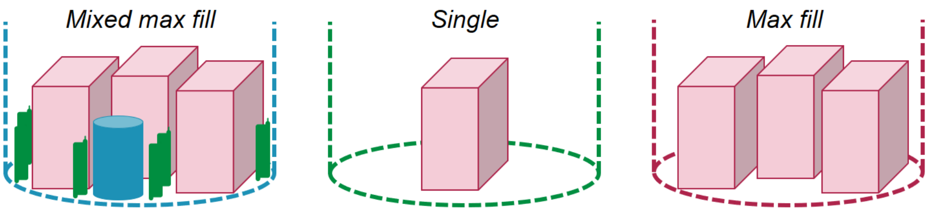


Figure 4.13. Batching strategies.

Having the next batch defined, the model gives the user the option to additionally revise the machine choice. Specifically, the *assign_build* method is provided with a function that aims to increase the use of an overall plates area that is discussed in section 4.2.3.1. This is expressed through a *plates_utilization* indicator that equals the ratio between the overall footprint of parts produced and the sum of effective areas of the plates (see Table 4.2) used in the process. Thus, a resulting indicator's integer value between 0 and 1 would show the efficiency of the plates' utilization in terms of their area use. When increased utilization mode is enabled, aiming to maximize the resulting ratio, the method, after selecting the machine, doublechecks the list of the machines with a minimum *builds_assigned* value and selects the one with the least build plate area that can fit the formulated list of parts. This is an essential consideration for the cases where the build formulated for a large machine consists of a relatively small number of parts (e.g., when printing the last parts of a given type with the *Max fill* strategy) and can be produced using another machine with a smaller build plate. When the final AM machine selection is made, the method books it in a corresponding administrating table by specifying the expected time of print initiation and completion using the rough estimates on build preparation duration and volumetric material-specific build rate.

Finally, the formulated batch is documented in the print program tables, specifying the data on build ID (essentially, the serial number of the build), types of parts included, their quantity, and the selected machine. Then, the method fills in the *Workpieces* table – an instructing list for the *Source* (an object that spawns the parts in the model) – with the bill of parts to generate for the defined build. As a result, the model creates the objects of those parts and of the machine-specific build plate and sends them to the build preparation station.

4.2.3.5 *Simulating build preparation*

When the object of a first part in the build (according to the sequence) arrives at the build preparation (BP) station, the latter updates the list of parts to incorporate in the same build. This list specifies the types of parts and their quantities. Based on it, the entrance method of the BP object calculates the duration of the process that involves parts orientation and supports engineering. Here, duration definition follows a set of assumptions (see the complete list of cost model assumptions in appendix A5):

- It takes 30 minutes to prepare a part that has not been processed before.
- It takes 2 minutes to prepare a part processed before (i.e., to position a part on the plate in the same arrangement).
- It takes 5 minutes to prepare the build that has been processed before (i.e., retrieval from the database).
- The maximum duration of build preparation is 5 hours.

Upon completing the BP process, the parts from the list are combined into one assembly object that imitates an STL file heading to the AM machine. Before moving it, the BP's exit control method creates its mass attributes (total parts and supports masses), raft area and mass (with the assumptions on raft height of 5 mm, density fraction of 70%, and homogeneous mass distribution), and the footprint area. Also, the *BP_costs* method derives the associated labor and capital expenditures based on the processing time and then distributes them among the part types proportionally to their quantities. These cost values and the supporting information on durations for each part type are accumulated in Table 4.3. The BP cost rate assumptions include:

- the engineer's salary at a full-time equivalent (FTE) of 100%;
- the engineer's FTE (taken as 100%), i.e., the percentage of effort required to execute the BP operation;
- the license hourly cost rate.

The license hourly cost rate is calculated accounting for the cost of capital, i.e., the interest rate[36]:

$$\boldsymbol{BP\_capital_{per\ hour}} = \frac{\boldsymbol{BP\_capital_{annual} \cdot \left(BP\_maintenance_{annual} + \frac{(1+BP_{infrastructure_{annual}}) \cdot interest\_rate}{1-(1+interest\_rate)^{-1}}\right)}}{\boldsymbol{hours\_per\_year}}, \quad \textbf{(9)}$$

Where:

[36] The license cost rate formula (9) is based on the yearly depreciation cost formula described by Gee (2020).

- $BP\_capital_{annual}$ – is the annual retail cost of the software license (taken as 6,000 USD);
- $BP\_maintenance_{annual}$ – is the approximate annual cost of scheduled and occasional support on software operation expressed as a fraction of $BP\_capital_{annual}$ (taken as 0.2);
- $BP\_infrastructure_{annual}$ – is the approximate annual expenditure on hardware (i.e., the workstation) and power necessary for the usage of the license expressed as a fraction of $BP\_capital_{annual}$ (taken as 0.3);
- $interest\_rate$ – the opportunity cost of spending liquid capital instead of investing it and thus earn a return on a fixed interest rate (taken as 0.05);
- $hours\_per\_year$ – the number of working hours per year (depends on the shift mode).

Table 4.3. Build preparation costs.

ID	**BP total** (USD)	**BP duration** (hours)	**BP Labor** (USD)	**BP Capital** (USD)
1	BP_1	$Duration_1$	BP_L_1	BP_Ca_1
…	…	…	…	…
N	BP_N	$Duration_N$	BP_L_N	BP_Ca_N

The resulting costs – both the breakdown (on labor and capital categories) and the total cost – are used in total costs derivation described in 4.2.3.11. Finally, after collecting the necessary information on the BP operations, the build, i.e., the control instructions for it (e.g., the toolpath employed by the machine represented with the STL file), is sent to the buffer of a designated AM machine.

4.2.3.6 Simulating printing

When the prepared build arrives at the AM machine, the entrance method *SLM_in* starts with defining the processing times, i.e., setup time, printing time, and the recovery time. The assignment of the setup and recovery times follows the normal distribution, which mean value equals the estimated expectation. First, it updates the *AMMs* table, which is a keeper of the operational information on each AM machine in the system; particularly, it tracks the amount of powder left in the powder feed hoppers, the number of builds assigned to each machine, and the respective times of completion. The setup time depends on the need to refill the hoppers. If the amount of powder is sufficient, then the setup time accounts only for the build installation time (taken as 20 minutes, i.e., the setup time mean is 20 minutes). If not, then the setup operation would include the hopper refill steps taking 25 minutes (i.e., the setup time mean is 45 minutes). It is assumed that at the start of the simulation, all the hoppers are full.

The processing time, i.e., printing, is defined as the sum of times spent on machine warm-up and inerting and on printing itself (i.e., layer-by-layer powder melting). The first summand is a machine-specific argument defined with the input data. The second summand is itself a sum of a pure powder melting time and the overall recoating time. The former is calculated by the entrance method following formula (10), and the latter is calculated with formula (11).

$$\boldsymbol{melting\_time} = \frac{\mathbf{10^6 \cdot 3600 \cdot (}\boldsymbol{mass_{parts}}\mathbf{+}\boldsymbol{mass_{supports}}\mathbf{)}}{\boldsymbol{build\_rate \cdot mat\_coef \cdot density}}, \tag{10}$$

Where:

- $melting\_time$ – is a pure powder melting time (in seconds);
- $mass_{parts}$ – is the total mass of parts in the build (in kilograms);
- $mass_{supports}$ – is the total mass of supports in the build (in kilograms);
- $build\_rate$ – is the machine-specific build rate taken for steel (in cm^3/h);
- mat_coef – is the material-specific multiplier for the build rate with respect to steel that is based on the work of Gee (2020);
- $density$ – density of the build material (in kg/m^3).

$$\boldsymbol{total\_recoat\_time} = \frac{\boldsymbol{build_{height} \cdot recoat\_time}}{\boldsymbol{layer\_thickness} \mathbf{-1}}), \tag{11}$$

Where:

- $total\_recoat\_time$ – is the overall time spent on recoating during printing (in seconds);
- $build_{height}$ – is the height of the build, i.e., the height of the highest part in the build (in micrometers);
- $recoat\_time$ – is the machine-specific time spent on one layer recoating (in seconds);
- $layer\_thickness$ – is the machine-specific thickness of one printed layer (in micrometers).

The recovery time includes machine-specific cool-down time and the time for build plate removal (taken as 15 minutes). Additionally, the machine requires cleaning with a user-defined cadence that is assumed to last 30 minutes (e.g., after each third build job).

When the machine completes printing and recovery, the exit method *SLM_exit* assigns the probabilistic as-printed and as-inspected values on the tracked internal quality (IQ) parameters for each part of the build. The assumption here is that each printer includes the in-situ process evaluation system, i.e., optical tomography system mentioned in section 2.2.3, capable of spotting the defects as porosity reliably. If this quality control shows the value of the tracked IQ parameter to be less than the lower specified limit, then the corresponding part is marked as a defect and immediately added to the production order for rework. The future version of the model is expected to include a more rigorous quality control system with the use of designated computer tomography machines.

After the machine cools down, the operator is called to uninstall the build and carry it to the buffer. Before this happens, *SLM_exit* calls the *Mat_costs* and *AM_costs* methods to account for the required expenditures in all cost categories (material, capital, labor, and consumables). The definition of material costs starts with the calculation of the wasted material mass. Some powder waste is inevitable, as in-process effects, e.g., spatter, denature the powder morphology and make it unsuitable for additional printing (Mounsey, Hon and Sutcliffe, 2016). This work uses the feedstock material (i.e., powder) waste rate of 9.5% reported by Walachowicz *et al.* (2017), applied to the mass of unmelted powder in the build (i.e., the overall mass excluding the parts and supports masses). The model assumes that the total mass of powder used per build is the mass required to clear the highest part in the build. The cost of wasted material is then distributed among different part types proportionally to their cumulative masses. Also, the raft material is distributed among the part types proportionally to their cumulative footprint on the build plate. Lastly, the cost of material spent on parts and supports is added for each part type.

The capital cost of printing is associated with the machine purchase cost; the model determines an hourly cost of ownership per machine according to formula (12)[37]:

$$\boldsymbol{AM\_capital_{per\ hour}} = \frac{\boldsymbol{machine\_cost \cdot (maintenance\_rate_{annual} + \frac{(1+infrastructure_{annual}) \cdot interest\_rate}{1-(1+interest\_rate)^{-lifetime}})}}{\boldsymbol{hours\_per\_year}}, \tag{12}$$

Where:

- $machine\_cost$ – is the retail purchase cost of the machine;
- $maintenance\_rate$ – is the approximate annual cost of scheduled and occasional maintenance as a fraction of $machine\_cost$;
- $infrastructure_{annual}$ – is the approximate annual expenditure on hardware and power necessary for the machine's usage expressed as a fraction of $machine\_cost$;
- $interest\_rate$ – the opportunity cost of spending liquid capital instead of investing it and thus earn a return on a fixed interest rate (taken as 0.05);
- $hours\_per\_year$ – the number of working hours per year (depends on the shift mode).

The resulting cost is then applied proportionally to the time the machine is occupied per the build-time calculation and set-up and cool-down times specified by the user. The cost per build is then assigned fractionally to each part according to the part's mass (here, mass is used as a proxy for a part's contribution to the overall build time).

The labor cost of printing is accounted for according to variable FTEs for operators' work during print supervision and setup. In setup, i.e., build exchange and cleaning operations, the FTE equals 100%, and

[37] The derivation of the hourly cost of machine ownership (12) is described by Gee (2020).

in supervision, it is taken as 15%. These costs are distributed among the part types according to their total masses as well.

The cost of consumables has several contributors which scale differently. Gas consumption scales directly with build time, as the model assumes a constant volumetric flow rate (expressed in L/hr) to a machine during printing and cool down; the same is valid for warm-up but with a higher flow rate. Cost is assigned according to the cost per L of gas. The cost of electricity is accounted for similarly based on the machine's hourly power consumption and the cost per kWh, which is taken as 0.1 USD/kWh according to (*Russia electricity prices, March 2020 | GlobalPetrolPrices.com*, 2020). Again, since mass is used as a proxy for the overall build time, the costs of gas and electricity per part type are scaled with its mass. The other consumable costs scale with the number of builds, irrespective of their duration, as some components are replaced either wholly (e.g., filtration units) or fractionally (e.g., the substrate upon which components are printed is surfaced between each build and, after a certain number of builds, is discarded) per-build.

Similarly to the BP methods, AM control methods store the material and process cost information in the corresponding matrices (see Table 4.4-Table 4.5) and then forward the build to the heat treatment stage.

Table 4.4. Material costs.

ID	**Material total** (USD)	**Material part** (USD)	**Material supports** (USD)	**Material wasted** (USD)
1	$Material_1$	$Material\_part_1$	$Material\_supports_1$	$Material\_wasted_1$
…	…	…	…	…
N	$Material_N$	$Material\_part_N$	$Material\_supports_N$	$Material\_wasted_N$

Table 4.5. Additive manufacturing process costs[38].

ID	**AM total** (USD)	**AM cap.** (USD)	**AM labor** (USD)	**AM cons.** (USD)	**BX cost** (USD)	**WUCD cost** (USD)	**Print cost** (USD)
1	AM_1	AM_Ca_1	AM_L_1	AM_Co_1	BX_1	$WUCD_1$	$Print_1$
…	…	…	…	…			
N	AM_N	AM_Ca_N	AM_L_N	AM_Co_N	BX_N	$WUCD_N$	$Print_N$

[38] "AM cap." denotes the capital costs of printing, "AM cons." denotes the costs of consumables, "BX" denotes build exchange, "WUCD" denotes machine warm-up and cool-down; the columns storing an information on overall BX and WUCD durations per part type are hidden.

4.2.3.7 *Simulating heat treatment*

Right before entering the furnace object to conduct heat treatment (HT), the entrance method *HT_in* defines the processing time based on the material of the build. In the current version of the model, it is the only factor considered for adjustment of HT duration; the steel builds are treated for 2 hours, the aluminum and titanium build for 1 and 2.5 hours correspondingly (these approximations were taken from the laboratory experience). In future work, the heat treatment schedule should also consider the build configuration, i.e., adjusting the heating and cooling schedule depending on the build geometry and mass if necessary. The times of build installation to the heating chamber and its removal are taken constant and each equal to 10 minutes. The cooldown occurs outside the furnace and lasts for one hour. The operator's FTEs are the same as in printing: 100% for the setup operations and 15% for furnace supervision. The costs of capital, labor, and consumables are calculated similarly to those of the printing stage based on HT quantitative assumptions given in appendix A5. The resulting costs are distributed in accordance with masses of parts and stored in the HT costs matrix, as shown in Table 4.6. The processed build is heading to the bandsaw for plate removal.

Table 4.6. Heat treatment process costs.

ID	**HT total** (USD)	**BX time** (hours)	**HT time** (hours)	**HT capital** (USD)	**HT labor** (USD)	**HT consumables** (USD)
1	HT_1	HT_BX_1	HT_time_1	HT_Ca_1	HT_L_1	HT_Co_1
…	…	…	…	…	…	…
N	HT_N	HT_BX_N	HT_time_N	HT_Ca_N	HT_L_N	HT_Co_N

4.2.3.8 *Simulating build separation*

The entrance method *BS_in* of the plate removal station calculates the sawing time necessary for build separation (BS) from the plate. The cutting time is driven by the build cross-sectional area (i.e., the raft footprint area) and derived based on the cutting rate input variable, which is taken as 230 cm^2/hr for all materials; this value is taken for Steel 316L solid profile based on (*Band Saw Blade Speed And Feed Calculator*, 2020). In future work, the cutting rate value should also consider the material type, its hardness, and the geometry; also, additional methods for plate removal such as wire Electrical Discharge Machining need to be provided. The capital, technician labor (at FTE of 100%), and consumables (electricity) costs of the plate removal operation are calculated in the same way as for AM and HT steps. An additional consideration here is the blade cost that is considered by adding a fraction of blade purchase cost (taken as 400 USD) equal to the ratio between the sawing time spent on a certain part type and the blade lifetime (taken as 20 hours). Since the cutting time is scaled with the cross-sectional area, the final costs are distributed among the part types proportionally to their total footprint areas; the resulting values are accumulated in the BS cost matrix shown in Table 4.7. After this step, the parts having the internal defects are directed to the defects' isolator, and the good parts are headed to the post-processing station.

Table 4.7. Build separation process costs.

ID	**BS total** (USD)	**BX time** (hours)	**BS time** (hours)	**BS capital** (USD)	**BS labor** (USD)	**BS consumables** (USD)
1	BS_1	BS_BX_1	BS_time_1	BS_Ca_1	BS_L_1	BS_Co_1
…	…	…	…	…	…	…
N	BS_N	BS_BX_N	BS_time_N	BS_Ca_N	BS_L_N	BS_Co_N

4.2.3.9 *Simulating post-processing*

At this stage, the parts are assumed to undergo a manual removal of the supports, complemented with the other necessary finishing operations (such as polishing or sanding). The part setup time follows the normal distribution with 3 minutes as the mean value, the standard deviation of 1 minute, and lower and upper bounds being 2 and 4 minutes, respectively. The processing time at this station is defined with the entrance control method *PP_in* by multiplying the overall supports volume on the part's post-processing complexity factor and divided on supports removal speed (taken as 30 cm^3/hr for any material). For the parts that get to the post-processing (PP) stage for rework, i.e., after quality inspection, the processing time is taken 1.5 times lower to imitate the learning curve. For the finished parts, the PP step assigns the probabilistic values for the tracked GD&T parameters, i.e., as-manufactured (or as-produced) values, and sends them further to the quality inspection. Before this, the *PP_cost* method accounts for the costs of capital and technician labor (at FTE of 100%) spent on part processing, and updates the PP costs matrix shown in Table 4.8.

Table 4.8. Post-processing costs.

ID	**PP total** (USD)	**Setup time** (hours)	**PP time** (hours)	**PP labor** (USD)
1	PP_1	$Setup\_time_1$	PP_time_1	PP_labor_1
…	…	…	…	…
N	PP_N	$Setup\_time_N$	PP_time_N	PP_labor_N

4.2.3.10 *Simulating quality control*

In the LPBF-based workflow at hand, quality control (QC) is the final step devoted to visual inspection and optical metrology for dimensional and surface defects detection. In the current setting, it is assumed that this step takes 10 minutes for any part. However, future development of the framework is expected to define the step duration as a function of the type of inspection (with corresponding time scales) and the number of inspection objectives (i.e., the quantity of dimensional and surface parameters to track). This quality control results in identifying the parameters with the values beyond the interval between the lower and upper specified limits (i.e., LSL and USL). Specifically, the exit control method *QC_exit* assigns the as-inspected values for the tracked parameters following the normal distribution law, which mean value equals the as-produced value (assigned by the PP step), and the standard deviation (SD) is defined according to (13). Then, it compares this “measured” value with LSL and USL using different inequalities for two types of dimensions: shaft and hole. If the hole parameter value is lower than the LSL or the shaft parameter value is higher than the USL (i.e., if the part needs additional removal of the material), and there are no other defects identified, then the part is tagged as “rework” and sent to additional post-processing upon method completion. In the opposite case, when the hole parameter value is higher than the USL or the shaft parameter value is lower than the LSL, the part is tagged as “defect” with regard to this QC parameter. Such parts move to the specified defects isolator and are added again to the production order.

$$\mathbf{SD} = \frac{\boldsymbol{mean \cdot inspection\_error}}{\mathbf{3}}, \tag{13}$$

Where:

- $inspection\_error$ – is a cumulative factor hypothesized to account for the operational errors (such as geometrical errors, machine dynamic, probe related, and part compensation method errors), as mentioned in (Phillips, Borchardt and Caskey, 1993).

The formula (13) is designed to make sure that 99.73% of the measurements, i.e., three SD intervals, would lie within the measurement error of the control instrument. When making the *inspection_error* the input variable to the simulation, (13) can be used to find the optimal QC instrument justified through a tradeoff between its purchase cost and the resulting expenses on countermeasures and rejecting the good parts.

After performing the quality control measurements, the *QC_exit* method calls the *QC_costs* method to calculate the labor expenses at the engineer’s FTE of 100%. Though currently, the method does not account for any capital expenditures, e.g., instrumentation, it is deemed to be an important consideration for future development of the model. The resulting costs are collected with the QC costs matrix shown in Table 4.9.

Table 4.9. Quality control costs.

ID	**QC total** (USD)	**QC time** (hours)	**QC labor** (USD)
1	QC_1	QC_time_1	QC_labor_1
…	…	…	…
N	QC_N	QC_time_N	QC_labor_N

Additionally to the standard cost categories, the *QC_exit* method accounts for three quality-specific cost metrics collected at the total costs matrices shown in Table 4.12. The first two come from the Taguchi

Quality Loss Function (QLF), tracking the corresponding parameters on internal quality and GD&T. As defined by Taguchi (2004), the QLF is a "quantitative evaluation of loss caused by functional variation of a product." In this work, we use the "nominal-the-best" characteristic in accounting for losses incurred due to both internal quality and GD&T variation shown in Figure 4.14, as formulated in (14) by Taguchi (2004). However, in the case of internal quality, we do not add an extra cost if the resulting value is higher than required since there is no loss of quality. The third quality cost metric is called the *cost of countermeasure* and accounts for what the company may need to pay in case the defect passed to the customer would eventually lead to loss of reputation, legal action, or contractual penalties, as discussed by Muelaner (2019a, 2019b). This cost of countermeasure depends on the cause of the defect (i.e., specific to internal quality and GD&T parameters) and, for input simplicity, is taken equal to the cost of countermeasure undertaken by the customer in (14). The model relies on a user-defined input on the cost of countermeasure per quality parameter for each part type and adds up these costs for each accepted defect.

$$\boldsymbol{L} = \frac{\boldsymbol{A_0}}{\Delta_0^2} \cdot (\boldsymbol{y} - \boldsymbol{m})^2 \,, \tag{14}$$

Where:

- L – is the loss in dollars when the quality characteristic is equal to y;
- y – is the value of the quality parameter (i.e., length, width, concentration, surface finish, flatness, etc.);
- m – is the target value of y;
- Δ_0 – is the deviation at which functional failure of the product or component occurs;
- A_0 – is the cost of the countermeasure undertaken by an average customer (e.g., discarding, repairing, or replacing the product).

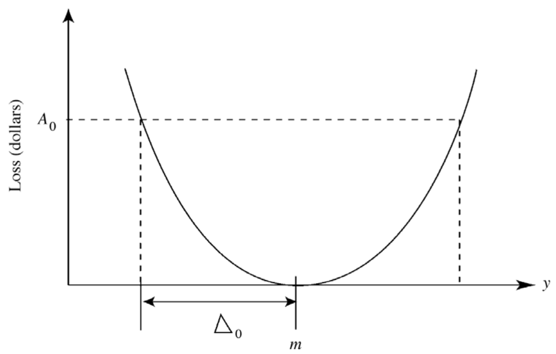


Figure 4.14. Nominal-the-best quality loss function (Taguchi, 2004).

Thus, for each part going through the QC station, the model tracks the costs of quality losses due to deviation in internal quality and GD&T, as well as the costs of countermeasures to pay in case if the passed defect would be financially damaging to the consumer. Importantly, though the model does always account for these costs, their inclusion – selective or complete – into the total cost per part type is a user preference that depends on the chosen cost modeling approach. Moreover, since the model records the costs of producing each part, it naturally registers the costs of rejecting the good parts because of a measurement error. Monitoring these expenditures enhances the analysis on the cost efficiency of the chosen quality control instrumentation. As a result, this capability allows to conduct quality costing studies balancing the output quality, rework amount, inspection costs, and system throughput, as shown by Spedding and Sun (1999).

After accounting for the necessary costs and before issuing the part, the exit control method compares the number of parts produced (without the defects) with the necessary production volume. If all the necessary parts were manufactured, then it trims the simulation runtime to the current state and calls the terminating method *endsim* to calculate the necessary metrics and finish the simulation run. However, an important remark is that in the integrated modeling mode, this rule is adjusted to allow multiple manufacturing iterations during the product development process, as discussed in section 4.3.

4.2.3.11 Model output

The product of the model can be versatile depending on the user's needs. Being a time-based framework, the simulation can provide a variety of performance-related measures, such as daily throughput or equipment utilization. If the general efficiency evaluations per machine (e.g., percentage of time working versus waiting for being maintained) are available at any point during and after the simulation in the form of built-in object's attributes, the assessment of system-level characteristics and other indicators peculiar for research (e.g., manufacturing cost breakdown) need to be predefined manually. The performance metrics that need to be determined at the end of the simulation are usually based on the data collected throughout the simulation, i.e., using the cost matrices in Table 4.3-Table 4.9, and finalized in the *endism* method concluding it.

In the developed framework, when the *endism* method is called, it starts with exporting the lists of all parts requested (i.e., the initial production order supplemented with the parts ordered for rework) and successfully produced. These lists include information on when each part's object has been generated in the system by the *Source* object and when it was completed, i.e., sent to the final *Drain* object, which, e.g., imitates the shipping department. Tracking such information for all parts allows the model to determine the average lead times for each of the involved part types (available as a built-in output of the list of parts produced).

Then, the method sums up all costs to derive the necessary per part evaluations. It relies on the stage-related matrices (Table 4.3-Table 4.9) that have collected cost data on the process for the whole of the simulation run as described above. *Endsim* is programmed to add up the costs within two breakdown structures managed with two corresponding matrices (Table 4.10-Table 4.11). The first has its columns devoted to the workflow stages: additive manufacturing (including materials costs), heat treatment, plate removal with a bandsaw, post-processing, and quality control. Therefore, it would show how much does each stage of the workflow cost for each part type. Such information is useful to see which steps and technologies take a larger budget portion and to develop the corresponding cost reduction strategies. The second breakdown segregates the costs into selected before categories: capital, labor, consumables, and material. Following it, the user can find out which types of expenditures are the most critical to address. Additionally, Table 4.12 collects for each part type the quality loss costs, which are *QL_IQ* for internal quality losses and *QL_GD* for losses related to GD&T. It also collects the costs of countermeasures (*CC*), as suggested by Muelaner (2019a), and the idle time costs.

Table 4.10. Total costs breakdown by workflow stages.

ID	Total WF	BP total	AM total	HT total	BS total	PP total	QC total
1	Tot_WF_1	BP_1	AM_1	HT_1	BS_1	PP_1	QC_1
…	…	…	…	…			
N	Tot_WF_N	BP_N	AM_N	HT_N	BS_N	PP_N	QC_N

Table 4.11. Total costs breakdown by capital, labor, consumables, and material categories.

ID	Total Cat.	Capital	Labor	Consumables	Material
1	Tot_Cat_1	$Capital_1$	$Labor_1$	$Consumables_1$	$Material_1$
…	…	…	…	…	
N	Tot_Cat_N	$Capital_N$	$Labor_N$	$Consumables_N$	$Mateiral_N$

Table 4.12. Additional total cost indices.

ID	QL_IQ	QL_GD	CC	Idle
1	QL_IQ_1	QL_GD_1	CC_1	$Idle_1$
…	…	…	…	…
N	QL_IQ_N	QL_GD_N	CC_N	$Idle_N$

In this work, the idle time cost is an optional indicator intended to measure the expense of renting the machines when they do not actually contribute to parts manufacturing at a given moment. Particularly, this indicator aims to track an amount of inefficient expenditures in the system caused by machines staying idle while waiting to be maintained or operated. For example, machines may wait idle if their operation is contingent upon the execution of a previous production step that has not been completed, i.e., get stuck in a bottleneck. To account for that, the *endism* method accesses a built-in statistical data on temporal fractions that machines spent throughout the whole simulation run waiting to be operated, or being blocked by the next object in a system (i.e., in the bottleneck), or being in a “fail” state and waiting for maintenance. Then, the method sums up those values and subtracts the unplanned time portions; e.g., when the shift plan does not include the night time, the non-working machines are staying in a “waiting” state until the morning and increase the “waiting” state portion; those durations are not considered as contributing to the total idle cost. The resulting idle cost of the system is then shared among the part types proportionally to their average lead times, perceiving it as a part’s impact factor on the manufacturing system workload.

However, the consideration of idle costs can be omitted in an alternative costing strategy that expects having lower machines’ uptime rates. For example, the model can consider that machines process the objects during 65% of an overall available time-space, instead of a more optimistic, e.g., 80% assumption, leaving a 15% gap for the idle costs. If such lowered rate turns out to be undervalued, i.e., the system on average operates at rates higher than 65%, then the cost model, eventually, would not underestimate the total expenses. A guiding assumption here is that overestimating the production costs is less harmful to the project performance than underestimating them[39].

In addition to a detailed cost breakdown for each part type, the model can calculate other specific performance indicators helping to judge the system’s efficiency. Currently, based on the data collected for each part type and the system overall, the *endism* method outputs the following list of selected metrics:

- *Cost per 10 cc* – an indicator showing how much does it cost to produce ten cubic centimeters of good parts (USD/10cc). Derived as a division of the total cost spent on all part types multiplied by ten over the total volume of those parts.
- *Clean throughput* – an indicator showing the number of parts, excluding the defective ones, produced per day (parts/day).
- *Overall throughput* – an indicator showing the number of parts, including the defective ones, produced per day (parts/day).
- *Clean rate* – an indicator showing the portion of parts produced without the defects. Derived as a division of the *Clean throughput* over the *Overall throughput*.
- *Clean volumetric throughput* – an indicator showing the volume of parts, excluding the defective ones, produced per day (m^3/day).

[39] The presented reasoning is inspired by the author’s discussions with Jonathan Meyer, a Chief Product Officer for APWORKS GmbH. The author would like to express his gratefulness for this invaluable share of practical knowledge related to AM cost modeling strategies.

- *Overall volumetric throughput* – an indicator showing the volume of parts, including the defective ones, produced per day (m^3/day).
- *Clean volumetric rate* – an indicator showing the portion of parts produced without the defects. Derived as a division of the *Clean volumetric throughput* over the *Overall volumetric throughput.*
- *Average lead time* – an indicator showing the average time it takes for one part to complete all production stages (from build preparation to quality control), including non-working time (hours).
- *Total production time per part type* – an indicator showing the average time it takes for all the parts of the same type to complete all production stages (days).
- *Plates utilization factor* – an indicator of the overall fraction of effective plates areas used in the printing process. Derived as a division of the total footprint areas of parts printed (including the defective parts) over the total effective area of the plates used.
- *Value per 10 cc* – an indicator showing how much valuable cost is spent on average per ten cubic centimeters (USD/10cc). Derived as a subtract of the total *QL_IQ* and *QL_GD* costs from the total cost spent on all part types. This indicator can be used for quality loss analysis discussed by Taguchi (2004).
- *Overpay rate* – an indicator showing the ratio between the *Cost per 10 cc* and the *Value per 10 cc*. It can be used for quality loss analysis together with the *Value per 10 cc* indicator.

When combined with the results on average lead times or overall production times per part type, these metrics can yield the important tradeoffs for the system's techno-economic performance.

4.2.4 Exemplary studies enabled by the framework

This subsection demonstrates the framework's analytical capabilities on the abstract case. It shows how a set of planning decisions affects the technical and economic performance of an AM production facility. Specifically, it explores the influence of the following four parameters on parts costs and lead times: batching strategy, the number of printers, the number of furnaces, and the number of operators. The selected reference model of the LPBF machine is EOS M100, which has a cylindrical build chamber of 100 mm in diameter and 95 mm in height. First, we investigate the characteristics of producing one part type and then the production of a set of different parts.

4.2.4.1 *Producing a single part type*

In this study, we evaluate the cost of manufacturing an abstract part with given dimensions and material characteristics discussed in Table 4.1. The part specification is given in the last column of Table 4.14 (ID 9). The analysis shows the effect of employing additional AM machines or changing the batching strategy. The line graphs given in Figure 4.15a-b demonstrate how cost and lead time scale with production volume, respectively. When comparing batch strategies for manufacturing 100 parts with four LPBF machines, we observe that the *single* batch strategy raises the associated unit cost by 50% and reduces associated lead time by 26%. The simulation-based cost breakdown analysis for 100 parts production in Table 4.13 proposes three reasons. The first reason is a grown expenditure for wasted material induced by a higher material overturn and hence increased volume of powder to be recycled and wasted. The second factor is that the per-build costs are increased – as a function of more builds being needed to produce an equivalent number of parts – and each per-build cost is applied entirely upon a single part. Thirdly, the increase of idle time costs indicates unoptimized production flow.

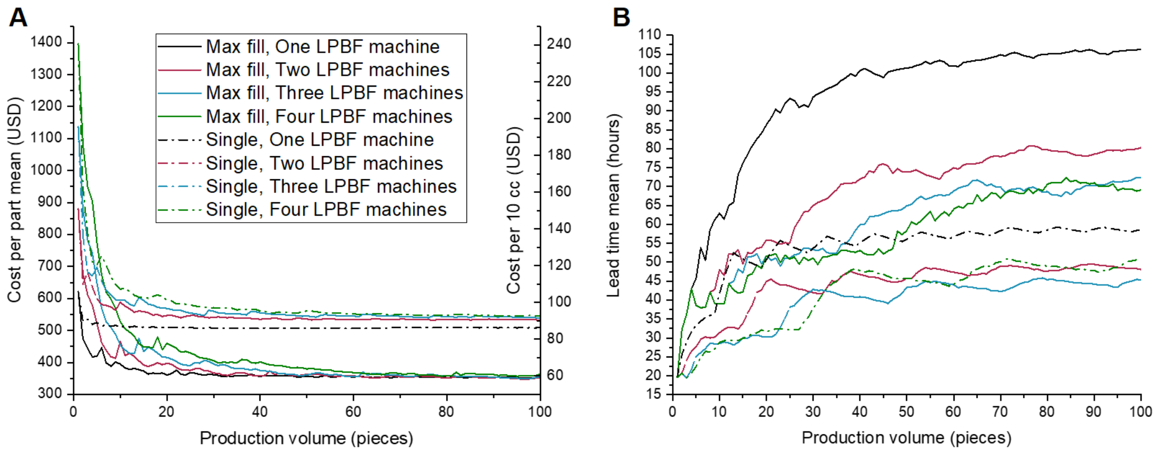


Figure 4.15. (a) Cost per part; (b) lead time versus production volume for a single part geometry.

4.2.4.2 *Producing multiple part types*

The second study simulates a manufacturing process for the production of nine parts types with different characteristics listed in Table 4.14 (based on Table 4.1). The component dimensions are comparable to small dental, medical, and jewelry components. Further, these components vary in quantity, post-processing complexity, and given days. From this experiment, we can observe the influence of the batching strategy on unit costs, individual cost elements breakdown, and component lead times. Figure 4.16 summarizes these values for the production system that utilizes only one printer. As in the first study, we observe the cost of a production rate increase when going from the *mixed max fill* strategy to the *single* strategy. Moreover, we observe that going from the *mixed max fill* strategy to the *max fill* strategy marginally increases the unit cost across most part IDs. In contrast, the average lead time significantly reduces.

Table 4.13. Cost per-part breakdown for *max fill* and *single* strategies employed in the production of 100 parts.

Cost constituent	Max fill strategy		Single strategy	
	Value	Share	Value	Share
Build preparation	$ 0.7	0.2 %	$ 0.2	0.04 %
Printing material	$ 30.9	8.8 %	$ 47.4	9.31 %
Printing machine usage	$ 157.4	44.7 %	$ 189.5	37.22 %
Printing labor	$ 73.7	20.9 %	$ 120.3	23.63 %
Printing consumables	$ 36.5	10.4 %	$ 40.3	7.9 %
Heat treatment	$ 8.8	2.5 %	$ 35.9	7.1 %
Post-processing	$ 30.8	8.8 %	$ 34.1	6.7 %
Idle time	$ 13	3.7 %	$ 41.5	8.1 %
Total cost	$ 351.8	100 %	$ 509.2	100 %

Table 4.14. The catalog of nine parts types.

↓ Parameter \ Part ID →	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**
Production Volume	8	20	18	12	15	10	10	10	5
Material					Steel alloy				
Length (mm)	40	10	20	15	5	45	20	25	60
Width (mm)	40	10	50	40	10	15	10	45	20
Height (mm)	40	70	30	40	15	15	10	55	70
Part Fraction[40]	0.3	0.5	0.3	0.1	0.7	0.6	0.6	0.4	0.7
Supports Fraction	0.1	0	0.2	0	0.05	0.1	0.1	0.3	0.2
Post-processing Complexity Factor	4	1	4	1	3	2	2	1	2
Given Days (days)	5	20	10	30	17	9	11	18	35

[40] Part fraction parameter defines a fraction that the part volume takes from the part's bounding box volume.

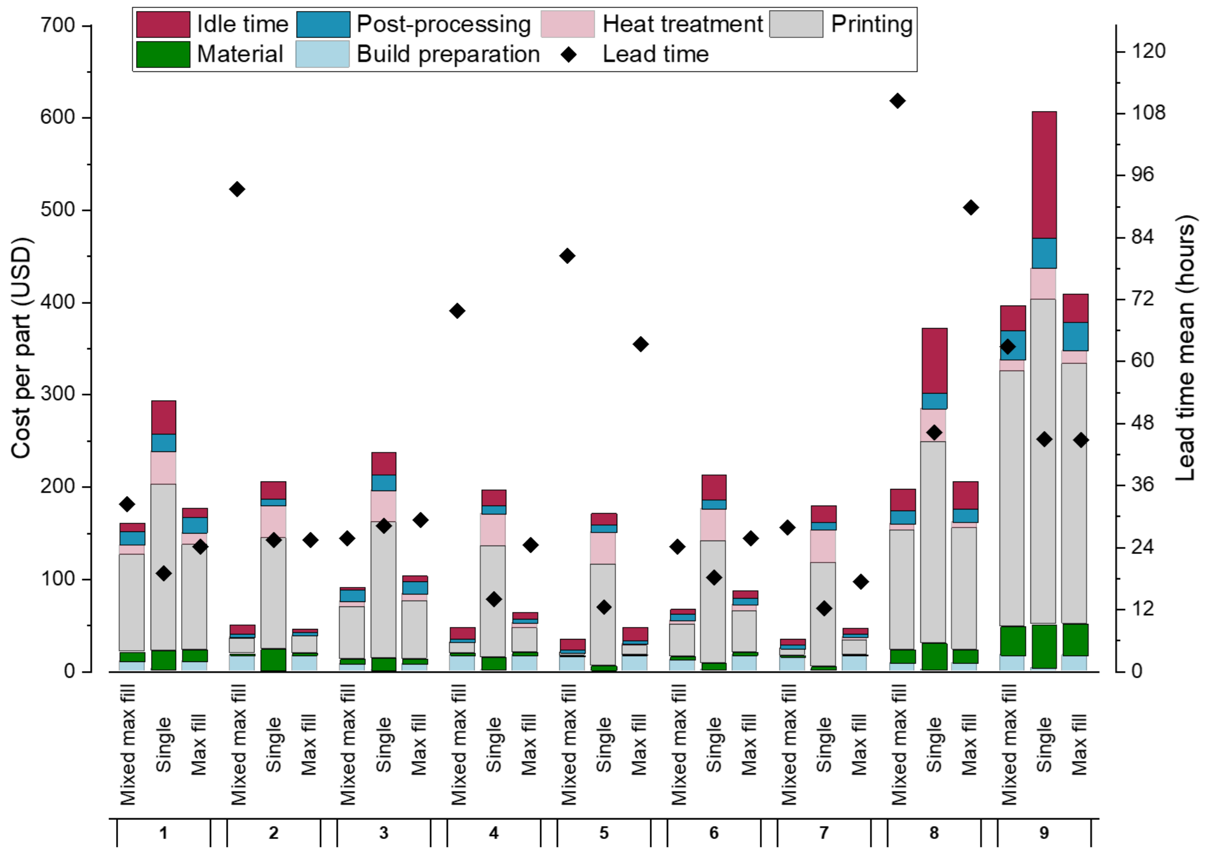


Figure 4.16. Summary of implications of build strategy on cost and lead time.

Going further, as shown in Figure 4.17, the tool can reveal tradeoffs in average cost metrics (represented as cost per cubic centimeter), average lead time (defined as the quantity-adjusted average of lead time means across part IDs), and the total production time (defined as the time required to produce all parts within the study). Moreover, the experiments expose that by increasing the number of furnaces or operators on the shop floor, the system can decrease both the lead and total production times. Presumably, by utilizing more LPBF machines yet keeping the same number of furnaces or workers, the production system experiences a bottleneck at the heat treatment step. This effect is demonstrated by the inversion points of the black and blue curves in Figure 4.17, bottom right, indicating the throughput blockages in the configurations with only one oven and more than three AM machines.

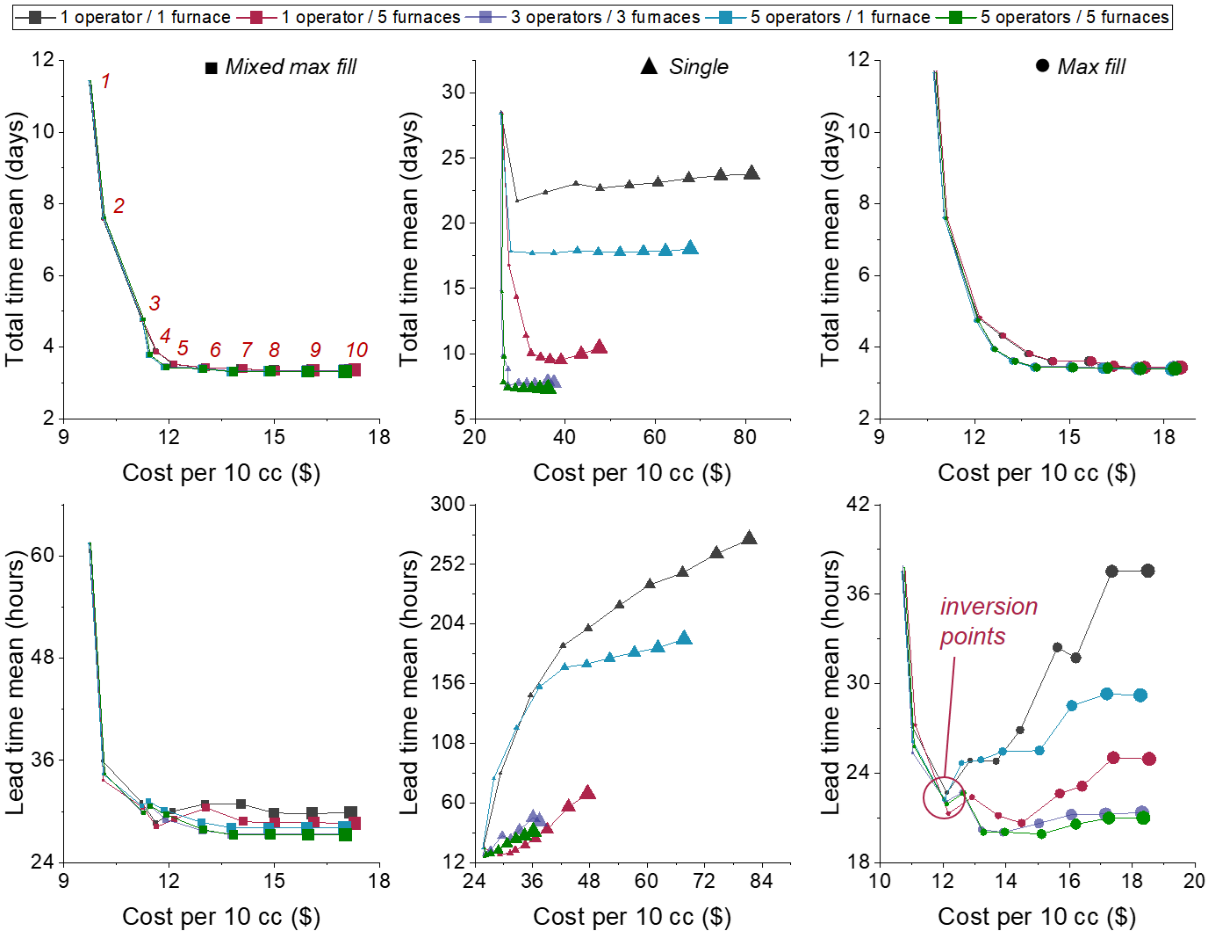


Figure 4.17. Comparison of average cost metric ($/cc) versus average lead time and the total time of production. The symbol size designates an integer value of printers utilized: from the smallest for one machine to the largest for ten machines.

4.2.5 Conclusion on the developed framework

As a result, section 4.2 presents the model-based simulation framework capable of depicting the production operations of an AM-based shop floor. It allows defining a particular context of a case, parametrizing the study with the variables of interest, running a series of experiments, and assessing the system's time and cost performance. The user can examine the influence of the variables related to the manufacturing system and process design described herein, such as the batching strategy, shop floor layout, numbers of machines, workers, or the shift mode. Alternatively, the framework allows the addition of new study-specific parameters that can be introduced relying on those prescribed by this work.

4.3 An integrated model-based analytical framework

After realizing the methods for simulation of PD and manufacturing operations, they can now be integrated into a single comprehensive solution, as shown in Figure 4.18. Since both parts have been implemented within the same modeling software, this task does not require excessive programming effort for their accurate merge. As a result, this combination simulates a complete product creation system running under a single time controller, which provides an absolute synchronization of the process events, and uses a common set of the underlying simulation rules that control the logic and behavior of the system elements. In other words, in approaching an integration of two components, this work builds on the very essence of simulation: creating a detailed representation of reality and how it evolves over time, making the use of powerful computational resources available today. Within the product creation process, we assume to have a generic product development team that runs the ICM process and orders the manufacturing services from an LPBF-based Service Bureau for components manufacturing.

As a result of merging two distinct methods into one, the framework obtains an emergent function of integrated analysis on engineering and manufacturing operations. It creates a novel value by enabling a comprehensive examination of multiple factors involved in the product creation process. This function brings together various aspects influencing the time- and cost-performance in PD and manufacturing domains and allows to investigate their compound effect. It is a critical advantage of the method as this way it accounts for multiple combinatorial outcomes that cannot be studied solely by either domain. At the organizational level, this emergent capability facilitates efficient coordination of the change data across all involved stakeholders and improves the system's capabilities in resources planning and expenditure.

As shown with the ICM reference process in Figure 4.3, the management of the change starts in the PD domain, which then triggers the operations in the manufacturing domain. In the same manner, the simulation model should demonstrate how the design change triggers production activities or vice versa in the case of a feedback iteration. Figure 4.18 demonstrates the implementation of an integrated modeling framework in Tecnomatix Plant Simulation™ 14.2 software (*Plant Simulation and Throughput Optimization | Siemens Digital Industries Software*, 2021). In it, the PD domain represented by the ".Models.LPBF.PDP" frame is integrated within the manufacturing domain represented by frame ".Models.LPBF" into a single model. As suggest the frame names, which reflect the paths to them, the PD domain model is embedded into the manufacturing model. This hierarchy has been chosen to reduce the integration effort by implanting a less compound model into a more complex one. Figure 4.19 illustrates the approach for integrated simulation based on the framework shown in Figure 4.18. It specifies the input necessary for PD and manufacturing domains characterization and shows the simulation output per one or several observations of an experiment.

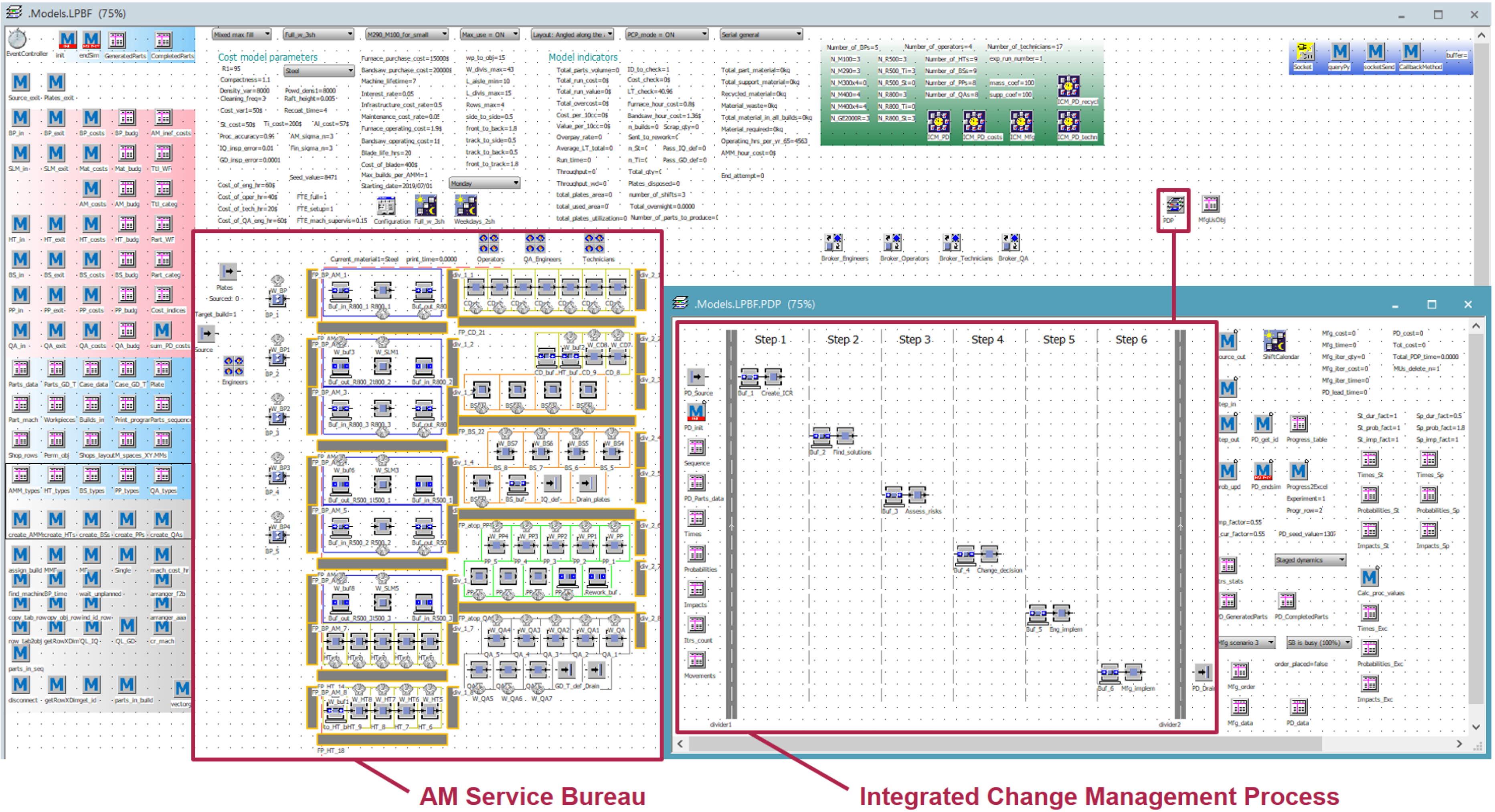


Figure 4.18. Integrated framework for Integrated Change Management simulation. The description of the major model objects is given in Figure 4.10.

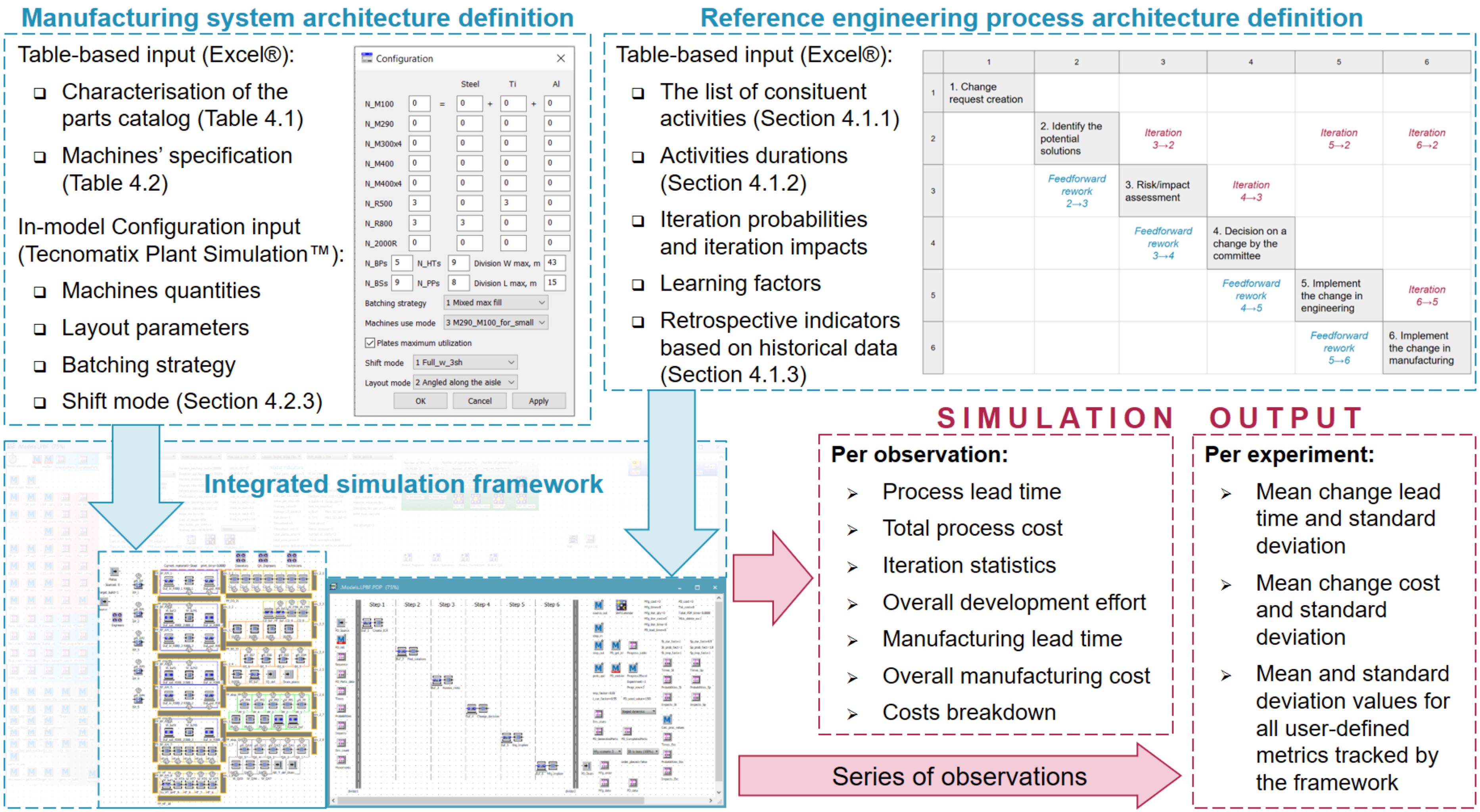


Figure 4.19. Illustration of the proposed approach for integrated simulation across the product development and manufacturing domains.

At a high level, we can summarize the concept of operations for the developed system with five major stages of operation:

1. The user defines the input data for the specific case, i.e., simulation experiment, including the data on the product undergoing a change and the configuration of the product creation system (see sections 4.1.2, 4.1.3 and 4.2.3.1 for more details). If the objective is to run the series of experiments (with a specified number of observations per experiment), then the user would need to define the ranges for variation of the selected input parameters. For each experiment observation defined by the user, the framework executes the following four stages of simulation.

2. At the initialization of the simulation, the Service Bureau starts its operation. Depending on the input, it either stays idle and waits for the order from the ICM process or is busy with producing a typical set of components. After that, the ICM process commences and goes through the sequence of steps defined with the reference process input, starting with those in the PD domain.

3. When the activity "Implement the change in engineering" triggers the activity "Implement the change in manufacturing," the model simulates the creation of an order by the product development team for the service bureau. For this, the entrance method controlling the ICM steps, when called by step 6, defines a list of parts to prototype. In the service bureau, all parts go through the same sequence of manufacturing operations, as described in section 4.2.3 for the LPBF-based process.

4. When the service bureau completes the production of the requested set of parts, it outputs information on the costs of manufacturing iteration and the time it took. Then, the exit method controlling the ICM steps, when called by step 6, simulates the testing activity and defines the outcome of production. If the parts meet the specified requirements, then the ICM process proceeds to the conclusion; in the opposite case, the method sends the subsystem undergoing the change for rework at step 5, "Implement the change in engineering," or step 2, "Identify potential solution," depending on the probabilistic outcome in accordance with input data.

5. In conclusion, the framework provides the overall process report in the table format, which contains the following information:

    a. The initiation and completion times of the ICM process including the date and day time data.

    b. The change lead time, i.e., the difference between the completion and initiation times.

    c. The iteration statistics, i.e., at which steps did the ICM process make the iterations and how many.

d. Manufacturing lead time, i.e., the calendar time it took to produce the necessary list of parts.

e. Overall manufacturing cost spent on all manufacturing iterations.

f. Overall PD effort, i.e., total FTE, and cost, i.e., the product of the total FTE and engineer's hourly rate.

g. Total cost of the project as the sum of manufacturing and PD effort expenditures.

h. Manufacturing cost breakdown to categories described in Table 4.10 and Table 4.11 separately for each production iteration.

Finally, such a framework can provide the functionality necessary to quantitatively study the combined influence of PD and manufacturing planning decisions on the system's performance in the AM context. The next chapter demonstrates the framework use case with possible analytical studies and thus validates its capabilities.

Chapter 5

Framework use case and validation

This chapter demonstrates the realistic case of using the framework described in Chapter 4 for Integrated Change Management (ICM) in the Additive Manufacturing (AM) context. It includes the description of the case context, specification of the change scenario, and the study of the planning decisions in product development (PD) and manufacturing domains. It shows the results of the series of trade-offs that investigate various factors rising from different managerial decisions related to PD and manufacturing operations. At the end, it summarizes the impact of the various factors and parameters on the techno-economic efficiency of the AM-based product creation system.

5.1 Use case context

The purpose of the use case is to demonstrate the application of the developed framework in studying the integrated change management process in the AM context and thus validate its analytical capabilities. The original case study data has been provided by Dr. Clement Fortin (Skoltech) and Dr. Grant McSorley (École Polytechnique de Montréal) in the form of a Project Main Report (PMR), Executive Summary, and other supporting documents from the project phases between the Requirements Review (RR) and the Production Readiness Review (PRR). The executive summary of the project is available at (Eagle Star Aviation, 2015).

The project is based on the task of redesigning an aircraft pylon for installation of a new engine, as illustrated in Figure 5.1. As shown in Figure 5.2, the pylon's major subsystems include the Front and Rear Mount structural components, the Fire Wall, the Bleed Air System, and the Fire Detection and Extinguishing Systems. The project data includes information on the process of redesigning the subsystems, the design of the manufacturing process for the selected components, and information on the team organization. It also covers the timeline and budgetary limits, as summarized in Figure 5.3 (ACR stands for the Advanced Concepts Review, PDR for the Preliminary Design Review, and CDR for the Critical Design Review). This project was realized over a period of 7 months by 12 engineering students supervised by experienced aerospace engineers. The project was realized in a fully virtual environment supported by the Dassault Systems suite of applications (*3D Design & Engineering Software - Dassault Systèmes®*, 2021).

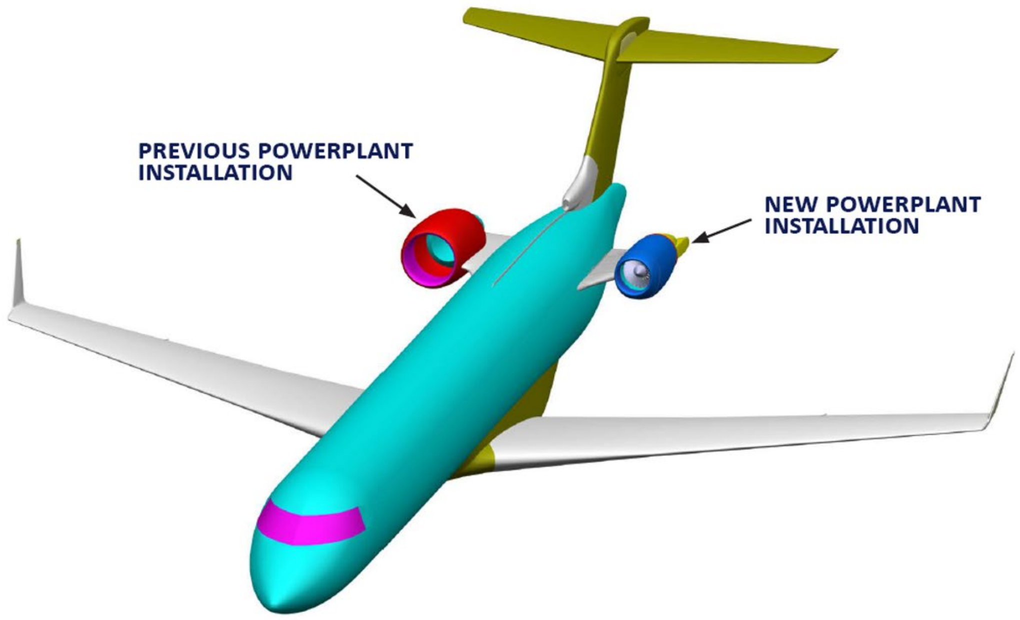


Figure 5.1. Installation of P&WC's PW305A turbofan on BA's CRJ700 aircraft; retrieved from (Eagle Star Aviation, 2015).

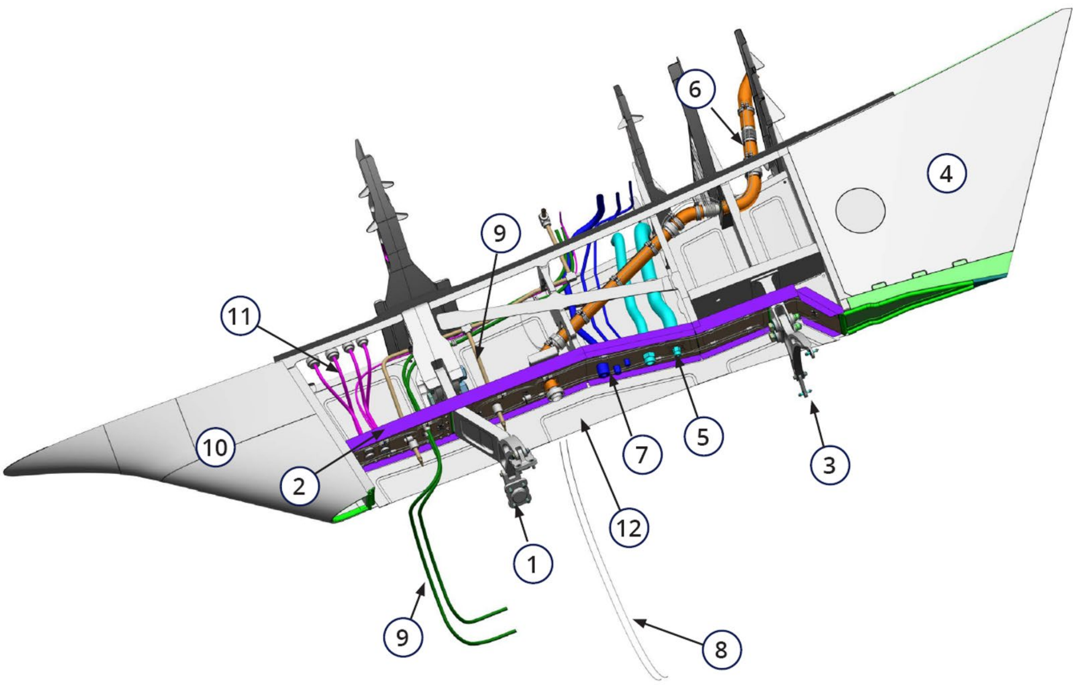


Figure 5.2. Pylon installation: (1) Front engine mount, (2) Firewall, (3) Rear engine mount, (4) Trailing edge, (5) Fuel lines, (6) Bleed air duct, (7) Hydraulic lines, (8) Fire detection, (9) Fire extinguishing system (FireX), (10) Leading edge, (11) Electric harnesses, (12) Skin and panels; retrieved from (Eagle Star Aviation, 2015).

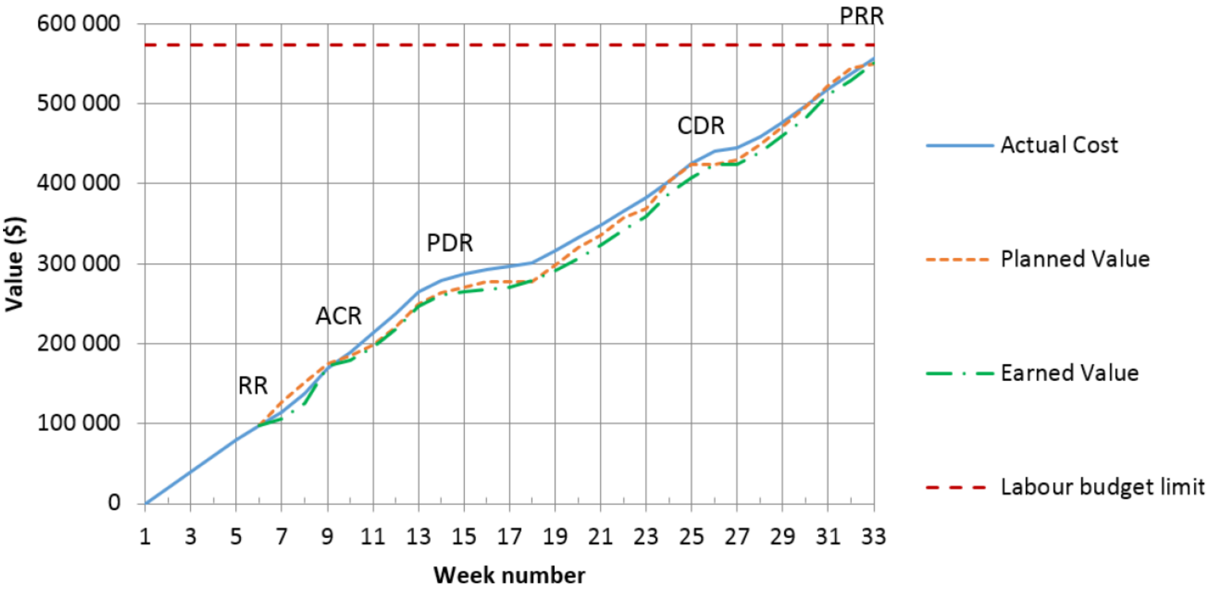


Figure 5.3. A general timeline and budget expenditure plan of the project; retrieved from (Eagle Star Aviation, 2015). The abbreviations include: *RR* for Requirements Review; *ACR* for Advanced Concepts Review; *PDR* for Preliminary Design Review; *CDR* for Critical Design Review; *PRR* for Production Readiness Review.

5.2 The change scenario

A use case for the developed framework is based on a specific challenge that the team has met at the PDR. The committee has found that the fuel lines were positioned below – and not above – the high-temperature bleed air duct, what might cause ignition in case of fuel leakage, and thus infringe the system safety. The team had to eliminate this design error by repositioning the components as demonstrated in Figure 5.4 before the CDR stage, hence imposing the financial and schedule constraints on the change project. From the overall project timeline (Figure 5.3), we can see that the team had 11 weeks between the PDR and CDR and planned to expend 200,000 USD on the product development operations during that period. Relying on the estimate of the change effort fraction, which according to Fricke *et al.* (2000) and Wasmer, Staub, and Vroom (2011) in average takes around 30-40% of overall PD effort, we can approximate the limits of the change duration and budget being four weeks (with five working days, eight hours each) and 80,000 USD respectively. The requested design change demands the engineering and manufacturing activities, which need to comply with the stated limits.

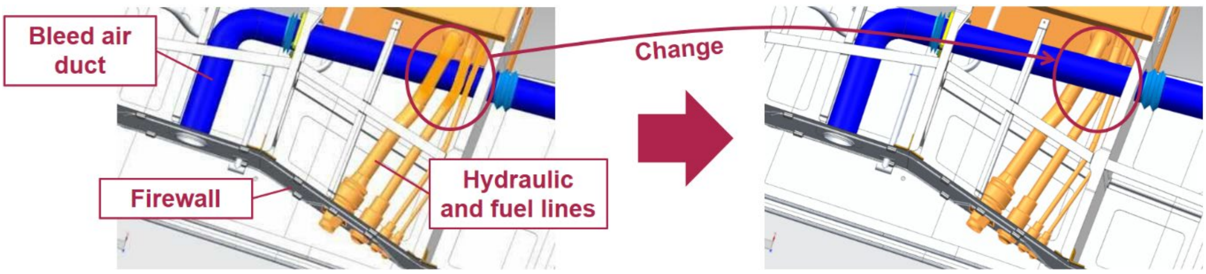


Figure 5.4. Use case change scenario: repositioning the hydraulic (6) and fuel lines (7) below the bleed air duct (2).

The whole process of managing the change, including the iterations, is covered by the ICM reference process discussed in section 3.1 and summarized with the high-level activities in Figure 5.5. It starts with the creation of the change request and goes through the identification of the potential solutions to the assessment of impact and risks associated with the requirements on system form, fit, and function (FFF), weight, cost, manufacturability, and certifiability. When the review committee arrives at a favorable decision on a change, the change order is passed to its implementation in engineering and then to manufacturing and testing of the necessary components set. In this work, we assume that the change in question affects the firewall, bleed air duct, and hydraulic and fuel lines. Some of these subsystems are initially planned to be produced in-house via traditional manufacturing methods, such as stamping, milling, casting, laser or plasma cutting, and, therefore, in case of the engineering change (EC) would require a corresponding in-house manufacturing change (MC).

	1	2	3	4	5	6
1	1. Change request creation					
2		2. Identify the potential solutions	*Iteration 3→2*		*Iteration 5→2*	*Iteration 6→2*
3		*Feedforward rework 2→3*	3. Risk/impact assessment	*Iteration 4→3*		
4			*Feedforward rework 3→4*	4. Decision on a change by the committee		
5				*Feedforward rework 4→5*	5. Implement the change in engineering	*Iteration 6→5*
6					*Feedforward rework 5→6*	6. Implement the change in manufacturing

Figure 5.5. The reference process for Integrated Change Management in the DSM form.

For research purposes, we consider an LPBF-based manufacturing process as a primary method for producing the necessary components in this use case. In such an AM context, we assume that the parts will be ordered at the service bureau operating based on the metal LPBF process. It conducts all the necessary stages of the LPBF workflow described in section 2.2.3 and calculates the cost and duration of producing the modified parts. The assembly operations are omitted as they are out of the scope of this work. Therefore, by implementing the change in manufacturing (step six), we mean producing certain parts set in the AM service bureau. Specifically, we concentrate on manufacturing and functional testing of the firewall and bleed air duct components, shown in Figure 5.6.

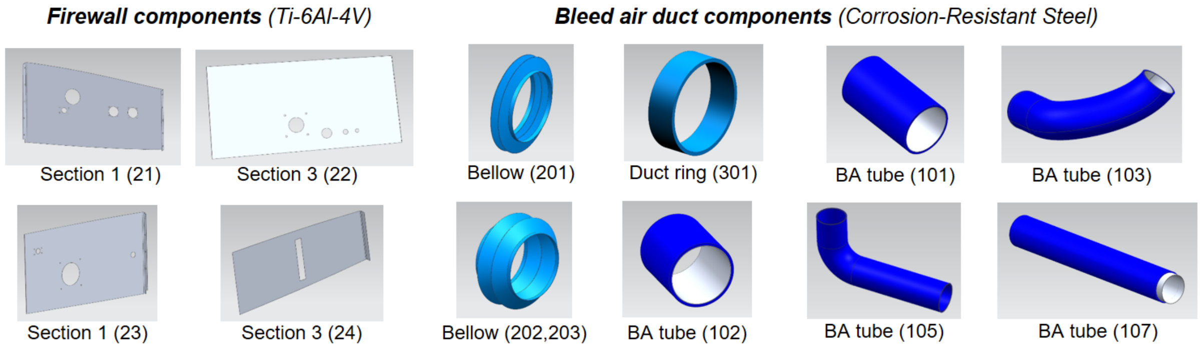


Figure 5.6. The set of the firewall (gray) and bleed air duct (blue) components to manufacture; parts IDs used in the framework are given in parentheses.

For the described use case, we demonstrate below the application of the developed integrated model-based framework in a series of studies evaluating the change cost and lead time. Table 5.1 provides the summary of the objectives and simulation input and output parameters to be examined in the respective studies.

Table 5.1. Summary of the objectives, simulation input variables, and simulation output metrics of the use case studies.

#	**Study objective** (a total number of experiments)	**Simulation input variables** (a number of alternatives)	**Simulation output metrics**
1	Define the change lead time distributions for pylon subsystems (11)	Subsystem-specific activities' durations and iteration probabilities	Change lead time distributions for each subsystem
2	Process dynamics influence on the change techno-economic performance (36)	The multiplier for iteration probabilities (6) The multiplier for activities' durations (6)	Mean change lead time Mean change cost Mean product development cost Mean manufacturing cost
3	Process architecture influence on the change techno-economic performance (2)	"Design for AM" step duration (2) "Manufacture the changed design and test" step duration (2) Iteration probabilities from the "Design for AM" step (2) Iteration probabilities from the "Manufacture and test" step (2)	
4	Powder recyclability influence on the change techno-economic performance (10)	Powder waste rate (10)	Mean change lead time Mean change cost Mean manufacturing cost
	Powder recyclability influence on the scope of process dynamics alternatives (72)	Powder waste rate (2) The multiplier for iteration probabilities (6) The multiplier for activities' durations (6)	Mean change cost
5	Influence of the parts mass change on the change techno-economic performance (16)	Change in part mass (16)	Mean change lead time Mean change cost Mean manufacturing cost
6	Influence of the support mass change on the change techno-economic performance (16)	Change in supports mass (16)	
7	Influence of the manufacturing system configuration on the cost of one manufacturing iteration (576)	Build batching strategy (2) Shift mode (2) Composition of the AM machines set (16) Layout configuration (9)	Mean cost of one manufacturing iteration

5.3 Study #1: Refinement of the modeling parameters using past change data

In the first study, we aim to evaluate and compare the lead times of pylon design changes triggered by its different subsystems. For this, we synthesize the project data into a set of retrospective indicators, which we use to refine the modeling parameters following the method described in section 4.1.3. In this work, we deduce the indicators based on the information about the pylon subsystems and their interrelation, as well as from the team structure. Then, we apply the part of the framework devoted to modeling the PD operations to see the dependence between the change effort and the selection of the subsystem that will trigger this change. Specifically, in each simulation run, we estimate the lead time of conducting the ICM process shown in Figure 5.5. Using the subsystem-specific indicators, we quantitatively adjust the durations of process activities and their iteration probabilities. In this study, the estimates of activities' default durations – including the durations of the "Implement the change in manufacturing" step – are assumed to be quantitatively defined by an expert estimate.

Based on the chapters on product overview and design in the project main report, and specifically on the "Part release sequence" section, we can represent the relationships between the pylon subsystems in the form of the Design Structure Matrix (DSM), as shown in Figure 5.7. The row items serve as the inputs and columns as the outputs of the design data. This means that the change in subsystem A triggers the change of the subsystems connected to it via column A. For example, the change in front engine mount (1) design would cause changes in firewall design (2) and rear engine mount (3).

Subsystem		1	2	3	4	5	6	7	8	9	10	11	12
Front engine mount	1	1	x	x									
Firewall	2	x	2	x		x	x	x	x	x		x	x
Rear engine mount	3	x	x	3									
Trailing edge	4				4								x
Fuel lines	5		x			5	x					x	
Bleed air duct	6		x			x	6					x	x
Hydraulic lines	7		x					7		x		x	
Fire detection	8		x						8	x			
FireX system	9		x					x	x	9			
Leading edge	10										10		x
Electric harnesses	11		x			x	x	x				11	
Skin and panels	12		x		x		x				x		12

Figure 5.7. Pylon DSM; "x" denotes the direct design relationship between the subsystems.

Based on this information, we can characterize the normalized change propagation factor *NPR*, reflecting the product complexity, by mapping the networking degree of the part under change between 0.1 and 1, such as shown in Table 5.3. In this work, we approximate the networking degree by the number of interfaces of a subsystem. The definitions of all retrospective indicators used in this study are summarized in Table 5.2; all indicators are normalized from 0.1 to 1.

Table 5.2. Definition of the retrospective indicators used in Study #1.

Indicator	Definition
NPR	Normalized change propagation factor reflecting the product complexity and showing the networking degree of the subsystem under change
NPE	Normalized factor reflecting the headcount of people involved in the same change request
NCR	Normalized collaboration resistance factor reflecting the difficulty of decision-making due to the distribution of involved people within a company
NRF	Normalized reappearance factor reflecting the proneness to iterations driven by the reappearance of people in the same change process for a selected subsystem
NCC	Normalized changes count factor reflecting the cumulative experience of re-engineering the subsystem by the company

Table 5.3. A summary of the normalized retrospective indicators for the pylon subsystems.

Subsystem	NPR	NPE	NCR	NRF	NCC
Front engine mount	0.2125	1	1	0.8	0.7
Firewall	1	0.46	0.4	1	1
Rear engine mount	0.2125	0.64	1	0.6	0.7
Trailing edge	0.1	0.64	0.7	0.5	0.6
Fuel lines	0.325	0.46	0.7	0.7	0.5
Bleed air duct	0.325	0.46	0.7	0.8	0.8
Hydraulic lines	0.325	0.64	0.4	0.4	0.3
Fire detection	0.4375	0.46	0.7	0.5	0.7
FireX system	0.4375	0.64	0.7	0.7	1
Leading edge	0.1	0.64	0.1	0.4	0.1
Electric harnesses	0.2125	0.1	0.4	0.1	0.2
Skin and panels	0.2125	0.64	0.7	0.8	0.3

Further, we create the Domain Mapping Matrix (DMM) to quantitatively map the other subsystem indicators related to product and organization domains. The pylon DMM, shown in Figure 5.8, displays which roles directly contribute to the design process of a particular subsystem. Out of it, we define the normalized factor *NPE* reflecting the headcount of people involved in the same change request (normalized from 0.1 to 1). Then, from the information on roles' affiliations to different departments demonstrated through color-coding the roles in the DMM, we can assess the normalized collaboration resistance factor *NCR*, normalized from 0.1 to 1. It reflects the difficulty of decision-making caused by the distribution of involved people within a company.

Subsystem\Organization		Project Manager	Configuration Manager	Vice-project Manager	Communication Manager	Structures Eng. 1 FFF	Structures Eng. 2 Materials	Structures Eng. 3 Electronics	Structures Eng. 4 Load Cases	Systems Engineer 1	Systems Engineer 2	Testing Engineer	Manufacturing Engineer 1	Manufacturing Engineer 2	Certification Engineer
Front engine mount	1	x	x	x	x	x	x		x			x	x	x	x
Firewall	2	x	x	x	x					x	x		x	x	x
Rear engine mount	3	x	x	x	x	x	x		x			x	x	x	x
Trailing edge	4	x	x	x	x	x			x				x	x	
Fuel lines	5	x	x	x	x		x		x	x			x		x
Bleed air duct	6	x	x	x	x					x	x		x		x
Hydraulic lines	7	x	x	x	x					x			x		x
Fire detection	8	x	x	x	x					x		x			x
FireX system	9	x	x	x	x					x		x			x
Leading edge	10	x	x	x	x	x			x				x	x	
Electric harnesses	11	x	x	x	x					x			x		x
Skin and panels	12	x	x	x	x	x			x	x	x	x	x	x	x

Figure 5.8. Pylon DMM; "x" denotes the involvement of a particular role in the subsystem's design process; colors denote adherence to the role to a given department within the organizational hierarchy.

Two other retrospective indicators – the normalized people reappearance factor *NRF* and the normalized changes count factor *NCC* (both from 0.1 to 1) – we approximate through the expert judgment of the former project supervisor. Table 5.3 summarizes the normalized indicators, which we use to refine the modeling parameters related to activities' durations and iteration patterns. The details of the method are given in section 4.1.3. Figure 5.9 visualizes this map to illustrate the differences between the subsystems.

During the project, each of the subsystems can trigger a change of different effort magnitude; therefore, having a map of justified expectations on each subsystem's impact is critical for a project planner. Following the approach proposed in section 4.1, we apply the part of the framework simulating the PD operations, along with the parameters refinement method, for lead time evaluations of the potential design changes going through the ICM procedure illustrated in Figure 5.5. Each simulation experiment is based on the subsystem-specific input of the retrospective indicators given in Table 5.3, which are used to calculate the model parameters during the initialization of the simulation. By running a set of observations – 200 per experiment, in this case – the model produces a distribution of the lead time characteristic for a particular change scenario.

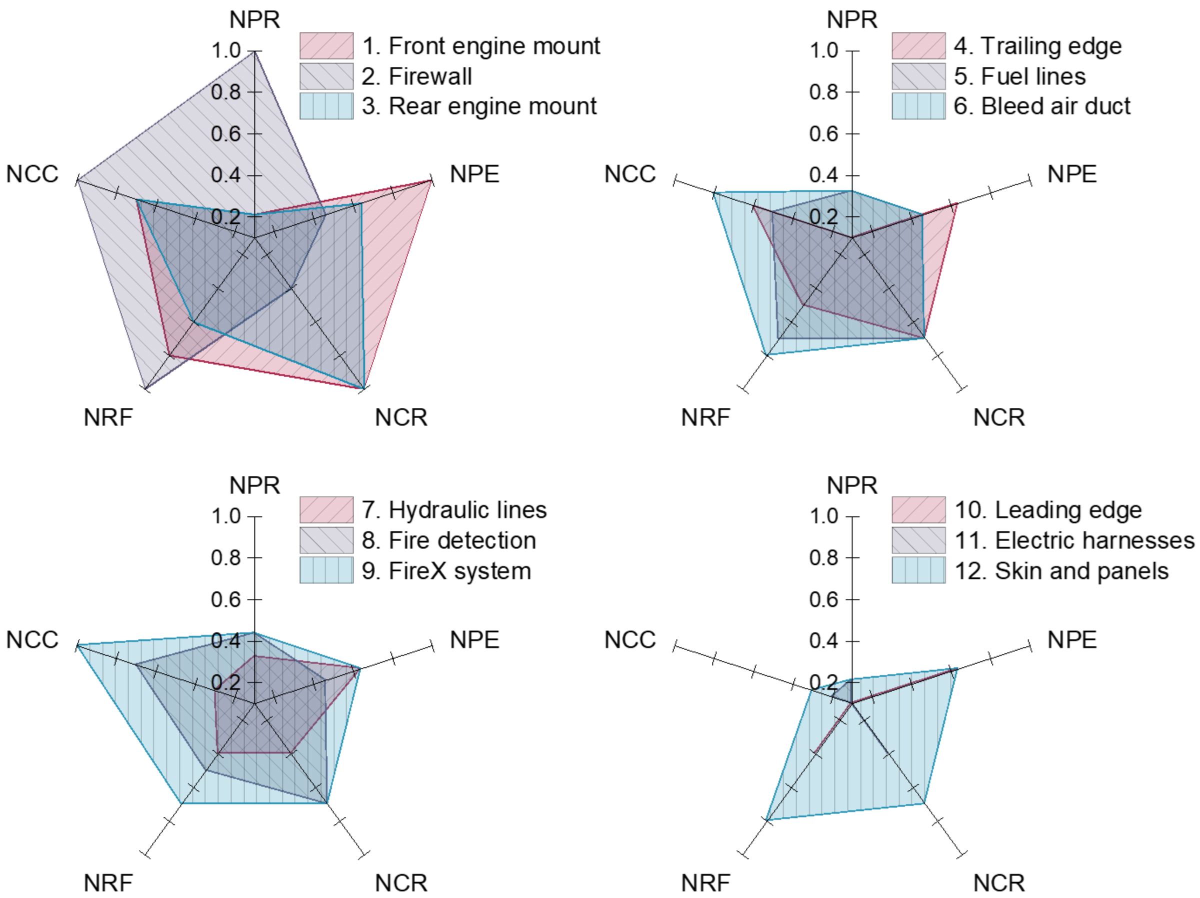


Figure 5.9. A map of the retrospective indicators for the pylon subsystems.

Figure 5.10 shows a summary of the simulation experiments for each subsystem. It is seen that the most critical subsystems in terms of potential effort allocation are the front mount, the firewall, and the fire extinguishing subsystems. These findings reflect reality as these subsystems are highly interconnected with the other pylon elements and require a high interdisciplinarity level to solve the design challenges. Accordingly, the least interrelated subsystems – such as the electric harness or the leading edge – are expected to demand the smallest amount of change effort. Also, the graph shows that some subsystems have a wider spread of the lead time distribution, e.g., see the values for the front engine mount (subsystem 1) between the 25th and 75th percentile; the change timelines related to such subsystems are expected to have lower reliability compared to those on, e.g., the hydraulic lines (subsystem 7).

With such analytics, the experts can save their time on ambiguous estimations and delegate part of their reasoning to the modeling framework that relies on past data. For a given scenario (Figure 5.4), we can infer that as long as the change involves only the hydraulic (subsystem 6) and fuel lines (subsystem 7), its lead time, on average, would be five days. If it would require reengineering the firewall (subsystem 2), the mean lead time can increase by eight days, making thirteen days total.

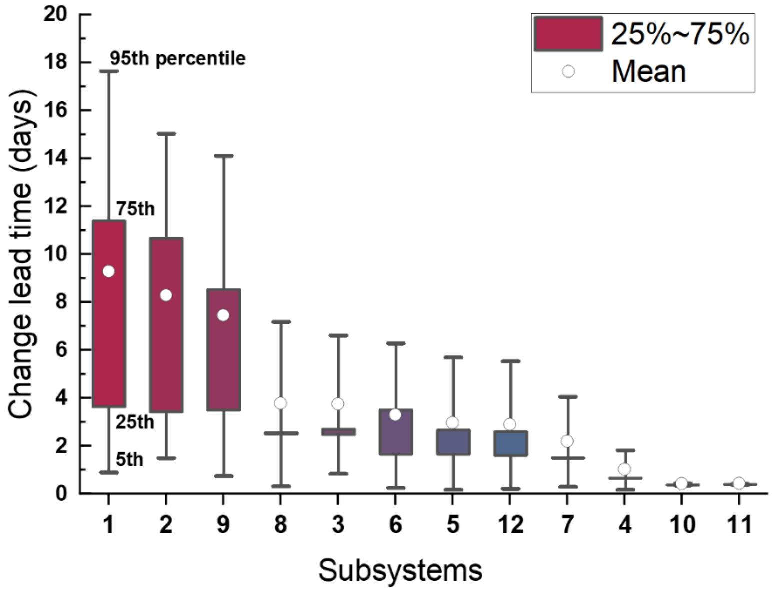


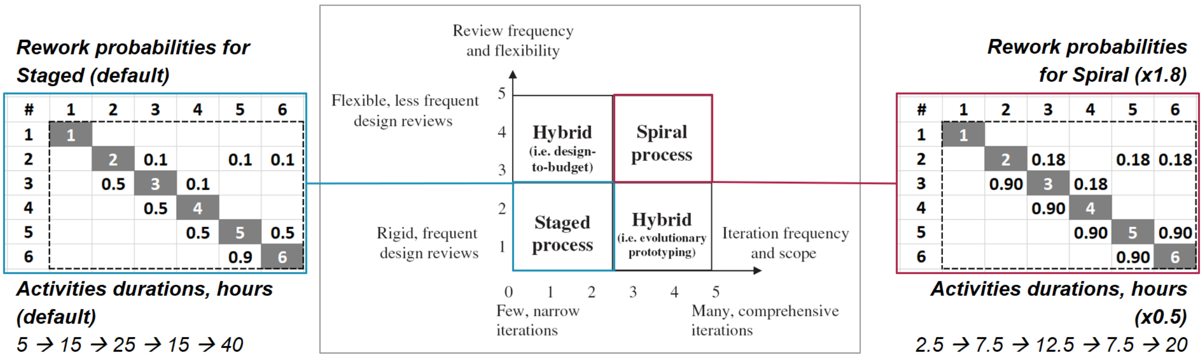
Figure 5.10. Simulation-based evaluations of change lead times for the pylon subsystems. Subsystems' numbers in the order of appearance on the X axis (left to right): (1) Front engine mount, (2) Firewall, (9) Fire extinguishing system (FireX), (8) Fire detection, (3) Rear engine mount, (6) Bleed air duct, (5) Fuel lines, (12) Skin and panels, (7) Hydraulic lines, (4) Trailing edge, (10) Leading edge, (11) Electric harnesses.

However, as mentioned in section 4.1.3 and experienced in the use case, the realization of the method demands a large volume of accurately captured data generated during the ECM process, as well as the precise techniques for processing the historical data. This type of information is generally available in industrial projects but is rarely used to decrease the uncertainty of future projects. This is seen as a significant advantage of the modeling approach proposed in this work.

Moreover, in this study, the duration of step six was assigned through expert estimation. An accurate simulation-based evaluation of the manufacturing process will be given in the following studies. The next study will investigate the structure of the reference process, which has not been considered here.

5.4 Study #2: Process structure influence

In this study, we analyze the influence of the process dynamics on the cost- and time-performance of the product creation system, using the framework for integrated analysis introduced in section 4.3. Specifically, we compare a range of the ICM process design options between the staged and spiral PD architectures discussed by Unger and Eppinger (2011). As shown with an example in Figure 5.11, the staged process has more thorough reviews within the activities, which, hence, last longer, and also has infrequent iterations between them. In contrast, the spiral process builds on the activities with shorter reviews but is more iterative.



#	1	2	3	4	5	6
1	1					
2		2	0.1		0.1	0.1
3		0.5	3	0.1		
4			0.5	4		
5				0.5	5	0.5
6					0.9	6

#	1	2	3	4	5	6
1	1					
2		2	0.18		0.18	0.18
3		0.90	3	0.18		
4			0.90	4		
5				0.90	5	0.90
6					0.90	6

Figure 5.11. Comparison of the PD processes based on common review and iteration characteristics; adapted from (Unger and Eppinger, 2011). The matrices on the left and right indicate the rework probabilities between the ICM steps shown in Figure 5.5. The activities' durations are given for the first five steps; the duration of the manufacturing step 6 is obtained from the simulation results.

To represent these two extreme cases for the ICM process shown in Figure 5.5, we use two sets of model input data shown on the left and right of Figure 5.11. Each set contains the tasks' durations and the DSM matrices for iteration probabilities. The default values (blue box on the left) are taken for the case in which all normalized retrospective indicators discussed in section 4.1.3 are equal to 1; the activities' durations are approximated with the expert judgment accounting for the limit in total change duration, i.e., four weeks. Accordingly, the staged process operates on the higher values for activities durations and lower values for iteration probabilities. The spiral process (red box on the right), on the contrary, uses the lower values for activities durations and higher values for iteration probabilities.

The configuration of the production system performing the manufacturing operations of step 6 includes three LPBF machines producing the steel parts and three machines for the titanium parts. The specifications of the reference machines used in this case are given in (*SLM®800*, 2020) and (*SLM®500*, 2020) correspondingly. The number of the heat treatment, plate removal, post-processing, and quality control stations, the operators, and the technicians equals 15 for each; this value is chosen to leave some reserve in productivity and avoid the bottlenecks, such as those discussed in section 4.2.4.2. For the same reason, there are five build preparation stations in the system. The facility operates on a "*Mixed max fill*" strategy (see section 4.2.3.4) and on a three-shift mode with 24/7 coverage, i.e., without any days off. The restrictions for layout generation are 15 meters for the maximum division length and 25 meters for the maximum division width (see section 4.2.3.3). Figure 5.12 illustrates the corresponding manufacturing system derived by the model (see Figure 4.10 for the definition of major objects used by the modeling framework).

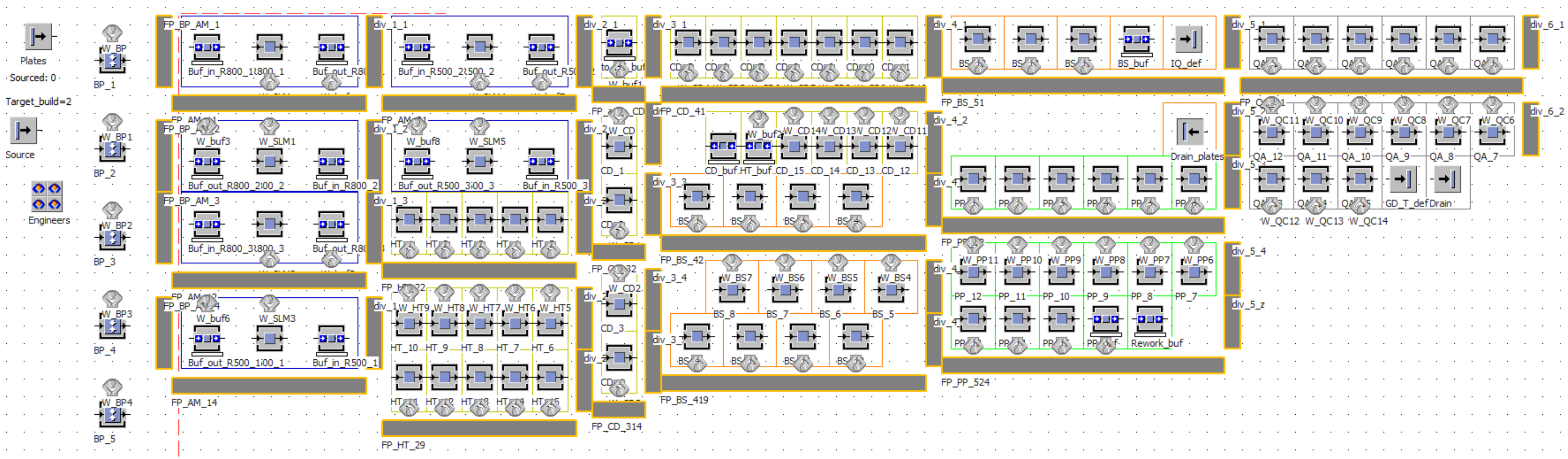


Figure 5.12. The manufacturing system configuration for studies ##2-7. The major in-model abbreviations are: *BP* for build preparation; *HT* for heat treatment; *CD* for cooldown; *BS* for build plate separation; *PP* for post-processing and manual supports removal in particular; *QA* for quality control and assurance; *FP* for foot path. The description of the major model objects is given in Figure 4.10.

One simulation run of the integrated framework, i.e., one observation of the experiment, provides the data on ICM process progress in time and resources expenditure. The numerated line in Figure 5.13 demonstrates the progress between the ICM steps within one observation simulated by the framework module shown at the top of this figure. The completion of each step of the reference process (Figure 5.5) is designated by a transition to a corresponding progress level. As such, the successful completion of step 1 corresponds to 5% of change management completion (Y axis), step 2 to 15%, step 3 to 35%, step 4 to 45%, step 5 to 75%, and step 6 to 100%. If an outcome of a certain step is a backward iteration, then the progress level after completion of this step is shown at a 2% lower level than that of a successful completion level (e.g., 73% for step 5 and 98% for step 6). On the example of one numerated observation in Figure 5.13, we can see two iterations after step six to step five and one iteration after step five to step two.

By running a series of observations for a particular process structure, we can observe its characteristic progress in time. To illustrate it, Figure 5.13 fills the space between the alternative progress patterns – i.e., different observations of the change managed with the same process architecture – with a light blue color. As a result, we get the process's progress footprint, marked by the colored region in Figure 5.13. In such representation, a darker color shade implies a higher iteration rate between certain process steps and time periods. Using this approach, we can illustratively compare different process architectures in terms of their lead times distribution and the frequency of iterations. Figure 5.14 shows the comparison of two options introduced in Figure 5.11: it is seen that in the given configurations, the spiral process (in red) performs better in lead time, on average, than the staged process (in blue). However, it is also seen that there are many more iterations in the spiral process, especially for manufacturing (after step six), which can require a higher budget. Therefore, we can infer that when determining the optimal dynamics of the PD operations, it is necessary to investigate the tradeoff between their speed and resulting budget expenditures.

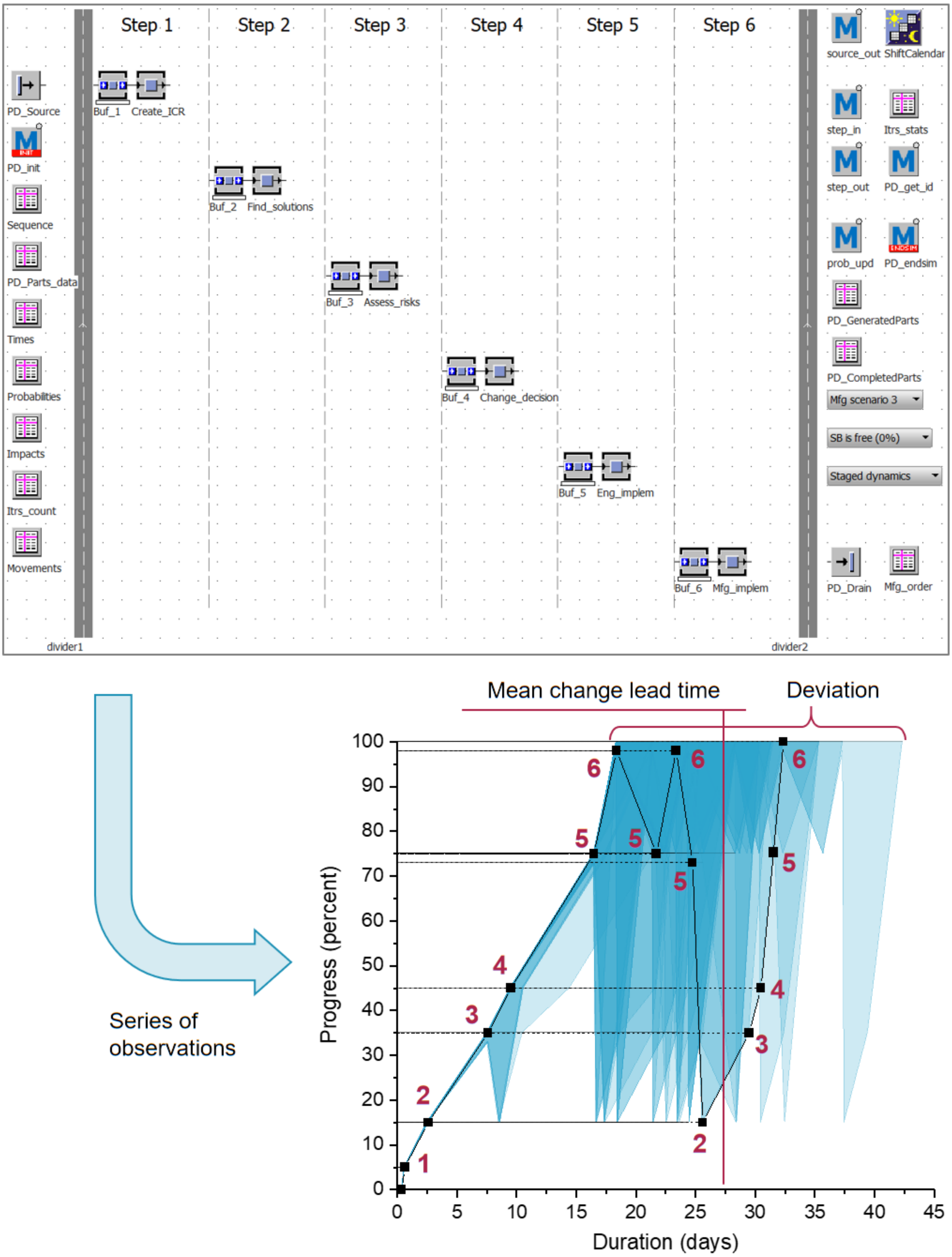


Figure 5.13. A simulation-based footprint of the process performance in lead time, illustrating the iterations along the change management progress. The red numbers in the Progress-Duration chart (bottom right) indicate the change progress (Y axis) as completion of the change process step – one of the six steps demonstrated in the modeling framework at the top – after a certain duration (X axis). The description of the major model objects is given in Figure 4.10.

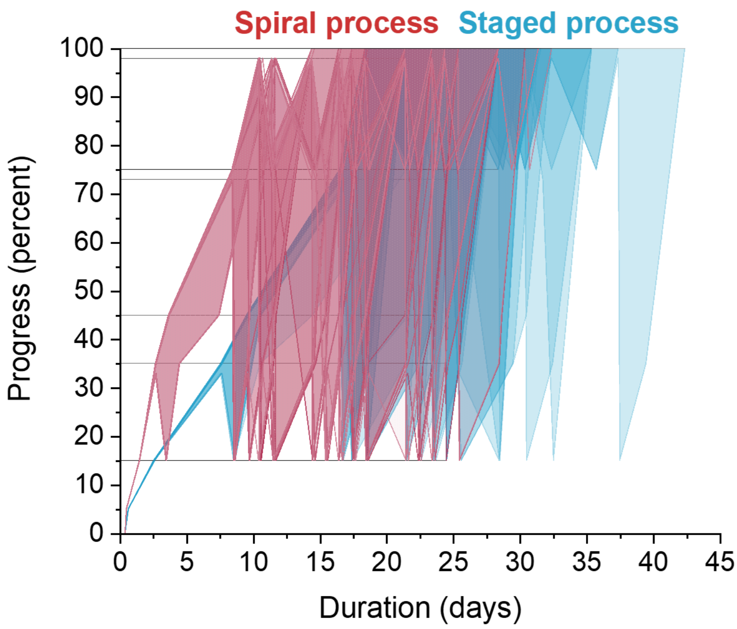


Figure 5.14. Comparison of the lead time footprints for the staged (blue) and spiral (red) process architectures.

To make such an integrated analysis, we leverage the configurability of the developed framework and its capability to accurately estimate the manufacturing expenditures. We design a series of experiments to capture the range of options between the two extremes of the ICM process, i.e., staged and spiral, and evaluate a techno-economic performance for each process architecture. The inputs to such a study are two multiplying factors shown on the X and Y axes of the chart in Figure 5.15. These multipliers modify the activities' durations and their iteration probabilities inherent to a default process structure – the staged process in Figure 5.11 – from 20% to 220% in increments of 40% correspondingly. That is, the iteration probability multiplier equal to 0.6 would reduce the probabilities by 40%, and the duration multiplier equal to 1.4 would increase the durations by 40%. As shown in Figure 5.15, such alteration of the process dynamics would make it closer to a staged process type, whereas the opposite change would make the spiral process type prevailing. The resulting process techno-economic performance – in terms of the change total duration, cost, and average product development and manufacturing expenditures – is then represented by a color code based on the case-specific budget and duration limits. As a result, we obtain 36 experiments, each with 200 observations that make 7200 simulation runs total[41].

[41] The total simulation runtime is 7.1 hour on one core with 2.90 GHz CPU and 32 GB RAM.

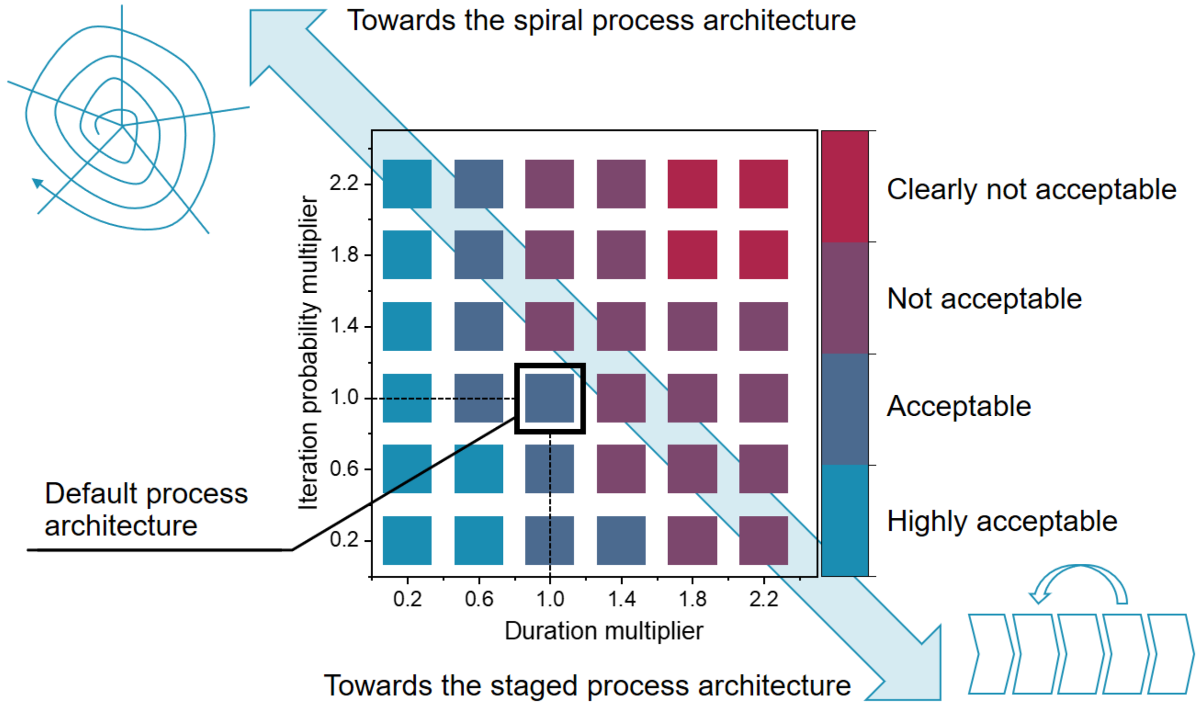


Figure 5.15. The comparison map for the range of process architectures.

Figure 5.16 evidently demonstrates the tradeoff between the process lead time mean and overall cost, including the manufacturing expenditures. The blue values indicate those process configurations that perform within the stated limits, i.e., 28 calendar days and 80,000 USD. This means that in varying the ICM process structure, the team may increase the default activities durations by up to 40% if the iteration probabilities are reduced down to 20% of the default values. However, the team cannot increase the default rework probabilities in any process configuration to stay within the budget limit.

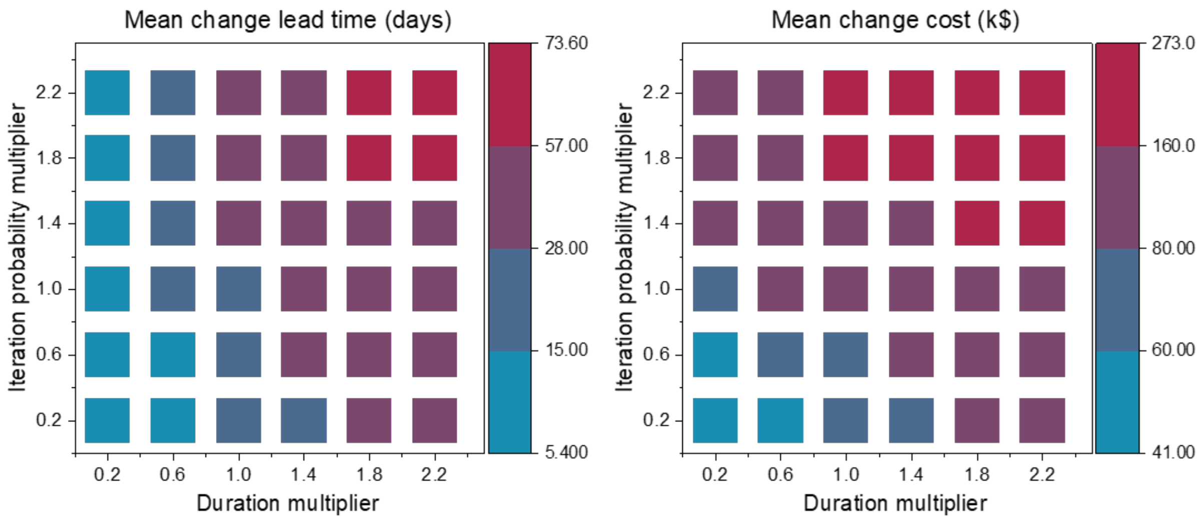


Figure 5.16. A color map of change lead times and costs for different process options varying in activities duration and rework probabilities.

Also, the framework can detail the cost structure: going one level down, we can look separately into the expenditures on manufacturing and product development operations, as shown in Figure 5.17. Based on the limits in durations and rework probabilities variations, we can see that the possible budget ranges for PD and manufacturing activities are 3,200-33,900 USD and 37,500-64,300 USD, respectively. The production cost can include several manufacturing iterations necessary for the process.

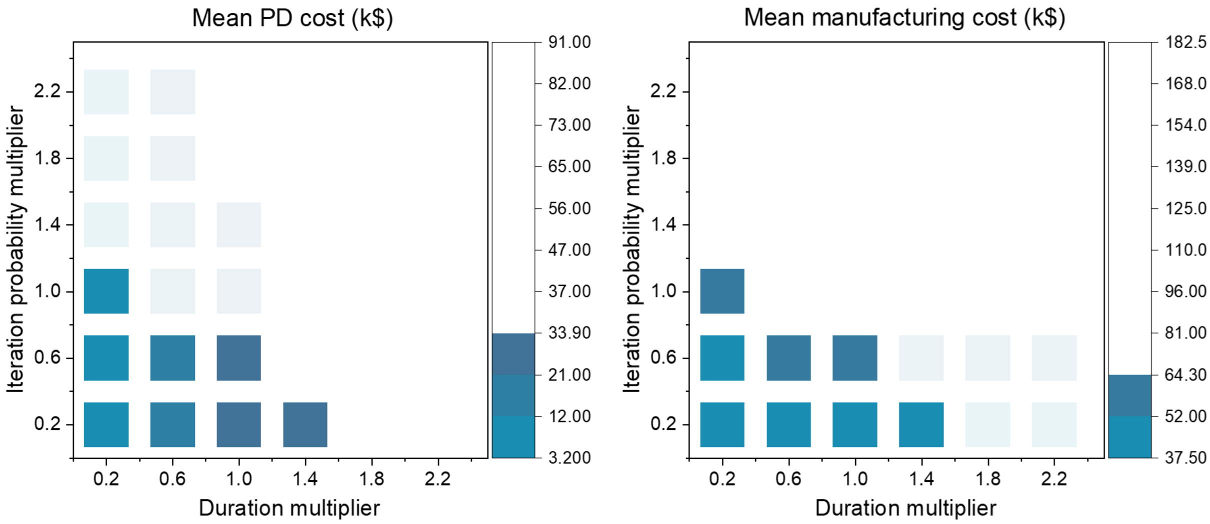


Figure 5.17. A color map of change costs spent on PD and manufacturing operations for different process options varying in activities duration and rework probabilities.

Taken in total, this study demonstrates a method to investigate the process architecture influence on the ICM techno-economic performance in the AM context. Through a series of integrated simulation experiments, we can quantitatively compare different process dynamics in terms of engineering and manufacturing operations costs and times. From this, the team can guide itself in choosing the process structure preferable in a given context.

5.5 Study #3: Influence of adding the AM technologist role

The third study is inspired by the interviews reported in section 3.2. Here we investigate the impact of adding the design for AM (DfAM) activity, executed by the *AM technologist*, into the generic ICM process, as shown in Figure 5.18. The purpose of this step is to enable a more accurate realization of the design and engineering intentions in manufacturing, and vice versa, given the immaturity of the AM technology. For this, a person experienced both in part design and execution of its printing process will take the as-design version of the component and modify it for better additive manufacturability. For example, he or she can change the round shape of the hole into the drop or diamond shape to reduce the amount of the supports or modify the build angle to achieve a better surface roughness. Also, this role can adjust the printing regimes, such as the laser power or scan speed, to achieve a better material quality. We assume that the duration of the DfAM step is equal to that of step five, “Implement the design change” (40 hours), and that its addition reduces the iteration probability after step “Manufacture the changed design and test” from 0.5 to 0.25. The configuration of the manufacturing system is given in Figure 5.12.

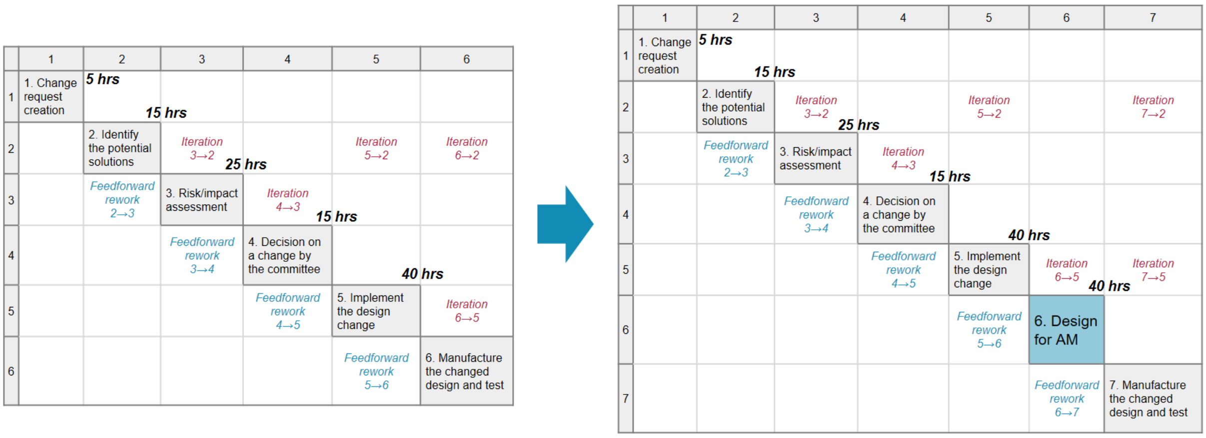


Figure 5.18. Adding the design for AM activity into the ICM reference process.

To compare the temporal and financial implications of DfAM activity introduction, in this study, we run two experiments – without and with the technologist role – each of 300 observations[42]. Figure 5.19 summarizes the result of the study with the box plots. We can see that the drop in iteration probability after the manufacturing step increases process reliability as the lead time deviation along the Y-axes reduces when the technologist is involved. It also reduces the mean manufacturing cost by 27% and mean total cost by 9% since the former outweigh the cost of PD operations. However, the lead time mean markedly increases (20%), indicating the tradeoff between change duration and its cost.

5.6 Study #4: Powder recyclability influence

In the next study, we aim to investigate the relationship between the change cost and the specific parameter of the manufacturing system, the powder recyclability. This characteristic is expressed through the fraction of powder that cannot be recycled and reused because of denaturation of its morphology as the result of in-process effects, such as the spatter. We choose the “unrecyclable fraction” parameter, i.e., the powder waste rate, to exemplify the influence that one manufacturing variable can have not only on the cost of production but also on structuring the related PD operations. The considered ICM process and the manufacturing system are given in Figure 5.5 and Figure 5.12 correspondingly. A default value of the waste rate is 9.5%, following Walachowicz *et al.* (2017). We run the simulations of the hypothetical systems with decreased waste, having 0.5% as the best-case value.

[42] The total simulation runtime is 28 minutes on one core with 2.90 GHz CPU and 32 GB RAM.

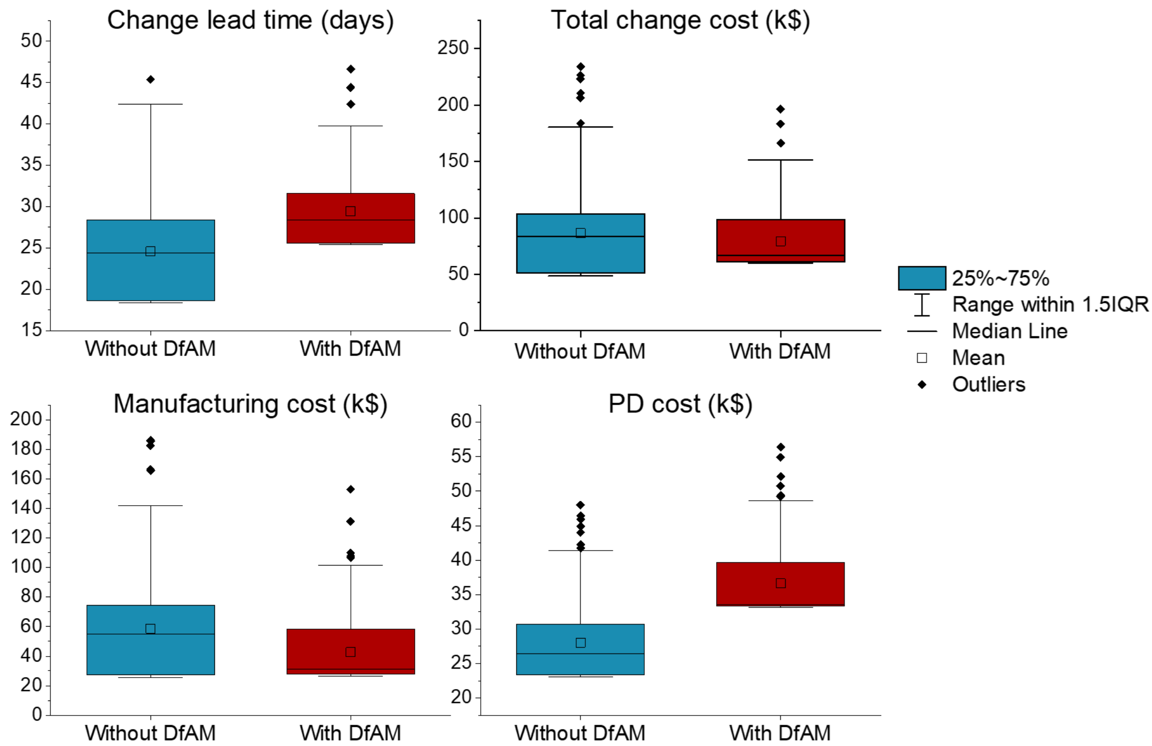


Figure 5.19. A time-cost comparison of the ICM processes without and with the design for AM (DfAM) activity to be performed by the AM technologist. IQR stands for interquartile range.

Figure 5.20 shows the cost breakdown generated by the framework for each of the prototyped components. Firstly, its top table reveals a high cost fraction of the material category in the case of a 9.5% powder waste rate. Since all parts are produced in the quantity of one and even the mixed max fill batching strategy does not fill the chambers in full, a potential explanation to this is the low utilization of the build chamber and, hence, a high volume of the material to recycle. Indeed, when comparing the original and best-case scenarios, i.e., the columns of top and bottom tables in a blue rectangle of Figure 5.20, we can notice a considerable decrease in material expenditure and in its fraction from the overall part cost. Further, looking at the set of 10 experiments with different unrecyclable fraction values[43], as summarized in Figure 5.21, we can see a decreasing trend in the cost of one manufacturing iteration and the total change cost. Going from 9.5% to 0.5% waste rate reduces these costs by 22% and 15% correspondingly. With the current set of assumptions, the trend of a change in the manufacturing iteration cost looks linear; the trend for the total change cost is not as determined, presumably, due to probabilistic outcome defining the average total number of manufacturing iterations within one observation. The change lead time did not show any trend related to the unrecyclable fraction; however, such dependence can appear after introducing any additional temporal assumptions on the recycling process.

[43] 10 experiments with 20 observations for each with total simulation runtime of 10.5 minutes on one core with 2.90 GHz CPU and 32 GB RAM.

Powder waste rate 9.5%

Part_id	Tot_per_part	BP_per_part	Mat_per_part	AM_per_part	HT_per_part	BS_PP_per_part	QA_per_part
21	1474.60	1.28	772.56	626.50	4.53	59.72	10.00
22	1541.93	1.28	777.67	683.48	5.08	64.41	10.00
23	1528.06	1.28	776.59	671.57	4.97	63.64	10.00
24	1504.23	1.28	774.54	649.24	4.75	64.42	10.00
101	2392.87	0.73	427.49	1846.83	1.82	105.99	10.00
102	1827.29	0.73	412.69	1330.49	0.00	73.38	10.00
103	6392.26	0.73	539.64	5768.45	0.00	73.43	10.00
105	6548.77	0.73	544.10	5920.38	0.00	73.55	10.00
107	6068.14	0.73	530.84	5453.02	0.00	73.54	10.00
201	989.68	0.73	389.45	515.84	0.00	73.66	10.00
202	2353.01	2.79	688.29	1606.64	0.00	45.30	10.00
203	659.19	2.57	151.36	479.26	0.00	16.00	10.00
301	1271.93	2.57	156.98	1086.60	0.00	15.79	10.00

Powder waste rate 0.5%

Part_id	Tot_per_part	BP_per_part	Mat_per_part	AM_per_part	HT_per_part	BS_PP_per_part	QA_per_part
21	1018.38	1.28	80.47	829.76	27.52	69.35	10.00
22	1122.96	1.28	85.58	919.62	30.23	76.24	10.00
23	1110.09	1.28	84.50	907.84	30.10	76.36	10.00
24	1086.41	1.28	82.45	885.68	29.87	77.12	10.00
101	2824.11	0.73	60.27	2537.17	73.52	142.41	10.00
102	2257.26	0.73	45.47	2019.99	71.66	109.40	10.00
103	6714.73	0.73	172.42	6365.80	65.53	100.24	10.00
105	6870.79	0.73	176.88	6517.68	65.52	99.96	10.00
107	6501.09	0.73	163.62	6145.61	71.65	109.47	10.00
201	2068.38	2.79	32.56	1878.17	57.08	87.78	10.00
202	1479.97	0.73	23.94	1264.29	71.65	109.36	10.00
203	699.72	2.57	11.31	638.90	13.89	23.05	10.00
301	1360.47	2.57	16.93	1293.59	14.18	23.21	10.00

Figure 5.20. A screenshot of the workflow cost breakdown into build preparation (BP), material (Mat), additive manufacturing (AM), heat treatment (HT), build separation and post-processing (BS_PP), and quality control (QA) operations. The cost values are given in USD units. The blue rectangle points to a significant decrease in material costs when reducing the powder waste rate.

This analysis is expected to bring value to the project manager reviewing the cost of implementing a more efficient system for powder recycling or melting process control. If the cost of such a system will be outweighed by the process savings within a reasonable time period, then its acquisition would be beneficial for manufacturing.

Moreover, the framework can allow us to quantify the influence of the powder waste rate on planning the PD operations. As illustrated in Figure 5.22, the increase of the recyclability ratio provides the PD team with more flexibility in tuning the dynamics of the ICM reference process. In the original setting, the change budget allows the team to increase the durations of the PD activities by 40% and does not allow to increase the rework probabilities (Figure 5.22 left). In the hypothetical case with a 0.5% powder waste rate, the team might increase the rework probability by 40% and PD durations by additional 40%, i.e., by 80% overall. This way, the study demonstrates the importance of considering the manufacturing decisions in integration with the engineering domain to account for many associated advantages and disadvantages.

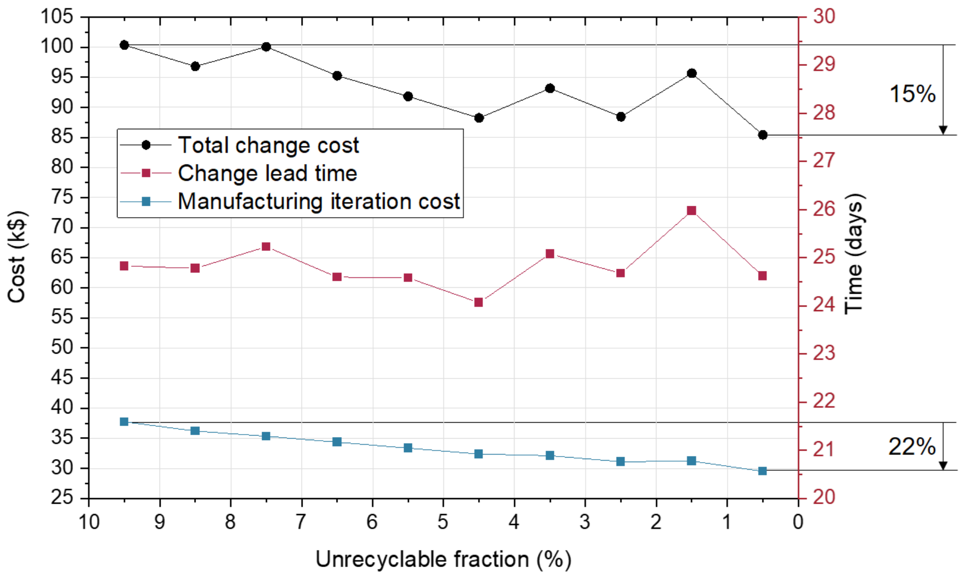


Figure 5.21. The influence of powder waste rate on the change costs and lead time.

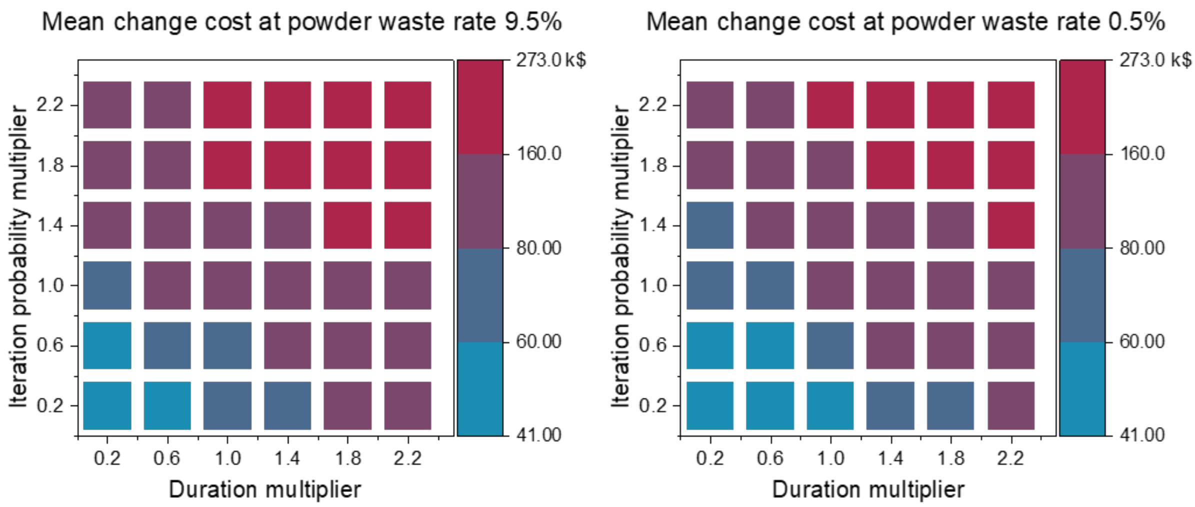


Figure 5.22. The influence of powder waste rate on process dynamics parameters.

5.7 Study #5: Influence of the change in part mass

This study aims to quantify the influence of a design change decision on the manufacturing system performance. Here we examine how the change in parts mass affects the cost of production and the duration of the ICM process overall. For this, we define a custom simulation input parameter that modifies the masses of the parts by multiplying their original values. Figure 5.23 shows this parameter on the X axis. The Y axis indicates the corresponding variation in the change lead time, the manufacturing total duration that covers all production iterations, and the manufacturing total cost, i.e. overall manufacturing expenditure during the necessary production iterations. The ICM process and the manufacturing system of study are given in Figure 5.5 and Figure 5.12 correspondingly.

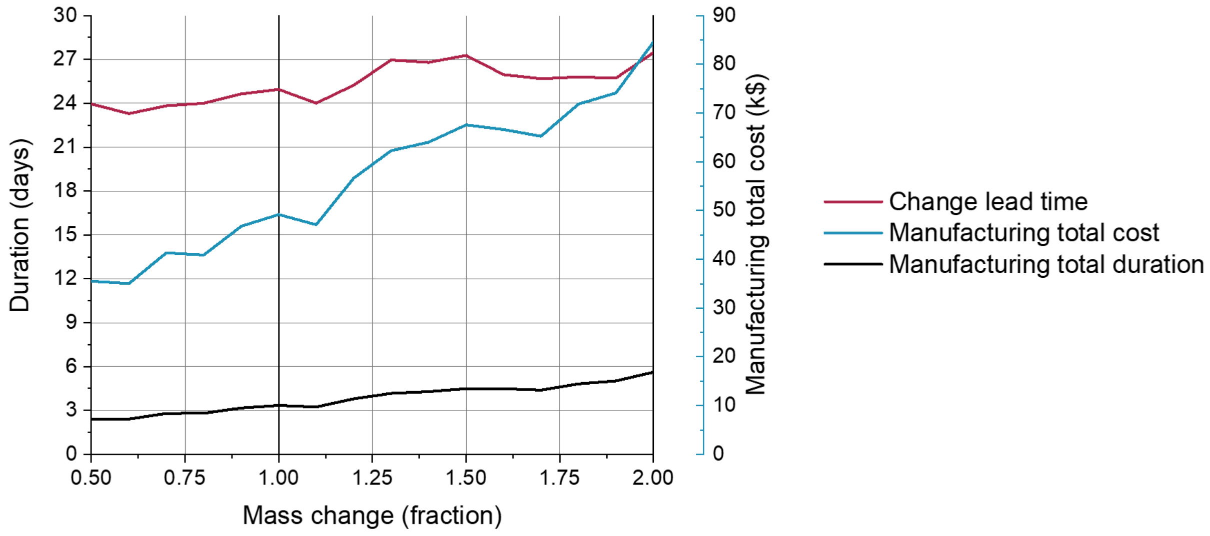


Figure 5.23. Influence of the parts mass change decision on the change cost and lead time; the dotted lines represent a visual approximation of the trend.

We can see that if the parts mass doubles, i.e., the mass change fraction increases from 1 to 2, then the manufacturing duration rises from 3.3 to 5.6 days, which is about a 70% growth. This relationship seems realistic since printing time has the largest share in the overall manufacturing duration and positively correlates with the volume of powder to melt. Correspondingly, the change lead time also increases, but not as much. Another big influence is on the manufacturing cost: since apart from extra material, a heavier build requires more time to be printed, it hence needs additional expenditures on the machine rent, labor, and consumables. A double increase in the masses of all components led to a 1.7 times increase in the total manufacturing cost. The fluctuations in manufacturing total time and cost may result from the probabilistic outcome defining the average total number of manufacturing iterations within one observation (see step 4 in section 4.3). Neglecting the fluctuations, we can suppose that the average trends in manufacturing duration and cost linearly correlate with the change in total part mass to produce.

5.8 Study #6: Influence of the change in supports mass

The current study continues a discussion from the previous by focusing on the supports mass change. Such request may be triggered by the engineers' intent to modify the part design or to try another orientation of the build. These decisions, in turn, can lead to the creation of additional thermal or mechanical supports to provide more structural rigidity or avoid warpage during printing. As a result, such a change would increase the ratio between the support mass and the part mass. In the same way as in study #5, we introduce a simulation input parameter modifying the supports mass – to the same extent for all components to prototype – and express it as a fraction of the part mass. By running multiple experiments with different values of the support to part mass ratio, we investigate its influence on the change lead time and costs. As in previous studies, we consider the ICM process and the manufacturing system given in Figure 5.5 and Figure 5.12 correspondingly.

Since, in the current case, the supports constitute only a small part of the total build mass, the impact from their change is noticeably less than that of the parts mass. As shown in Figure 5.24, a double increase in the supports mass raises the manufacturing duration by 13%, the change lead time by 5%, and the manufacturing cost by 13%. The primary reasons for that are the extra printing and materials expenditures, as well as the need for more post-processing, which is assumed to depend on the supports volume. As in the previous studies, the fluctuations in the shown time and cost metrics may result from the probabilistic outcome defining the average total number of manufacturing iterations within one observation. Neglecting these fluctuations, we can observe the linear trends in manufacturing duration and cost, which, presumably, correlate with the resulting ratio of the supports mass to the part mass.

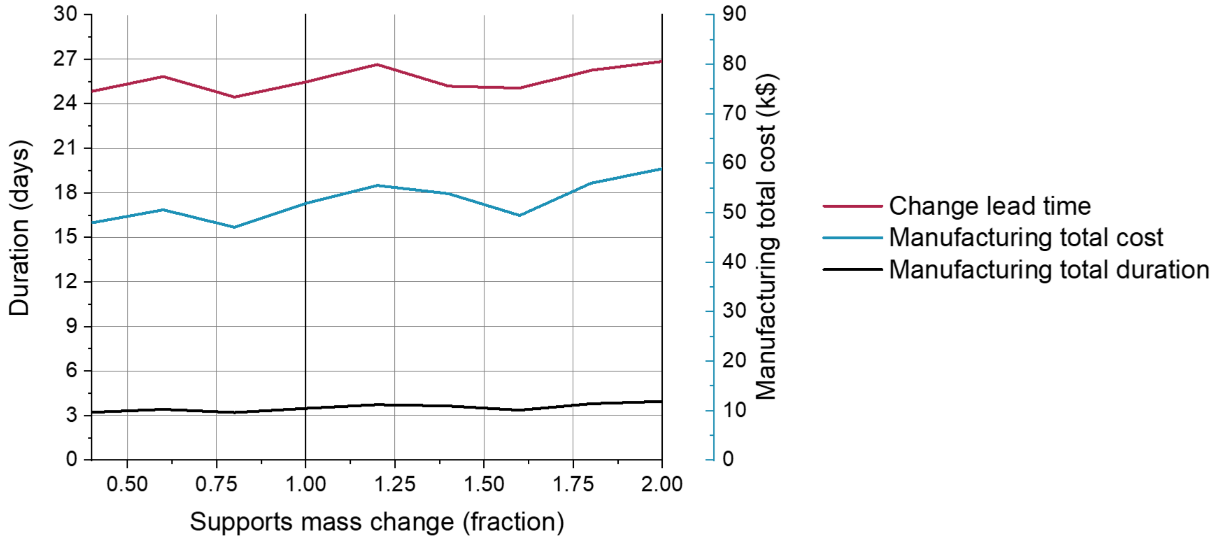


Figure 5.24. Influence of the supports mass change on the change cost and lead time; the dotted lines represent a visual approximation of the trend.

These results imply that the change in supports mass has a weaker influence on the process performance, and therefore has a higher chance to be implemented comparing to the change in part mass. Furthermore, this analysis also signifies a low added printing cost for the additional geometrical complexity of the component: the extra holes, inflections, and curvatures require more mechanical structures to hold the overhangs exceeding the critical angle. If the same change had been needed in the conventional setting, such as with milling or stamping, the readjustment of the machining process would have required significant expenditures on process re-design and procurement of new tooling. Still, a more accurate assessment would require further analysis of the influence of supports volume on the duration and cost of post-processing operations.

5.9 Study #7: Selecting a configuration of the manufacturing system

The final application of the framework is devoted to the definition of a more suitable manufacturing system configuration – in terms of the production lead time and cost – for executing the ICM process shown in Figure 5.5. For this, we compare the variety of possible system designs that differ in the batching strategy (*mixed max fill* versus *single*), the shift mode, the layout, i.e., in the width and length of the divisions (see Figure 4.12), as well as in the quantities of AM machines. Since in one production iteration, the manufacturing system would need to produce a single piece of each part type, the comparison of the single and max fill strategies is unnecessary. The rest of the configuration parameters match the manufacturing system given in Figure 5.12. All possible combinations produce 576 options. Simulating each with 20 observations per configuration, we can juxtapose them with the mean duration and the mean cost of one manufacturing iteration[44]. Figure 5.25 shows the result of this categorized by the batching strategy (left) and the shift mode (right).

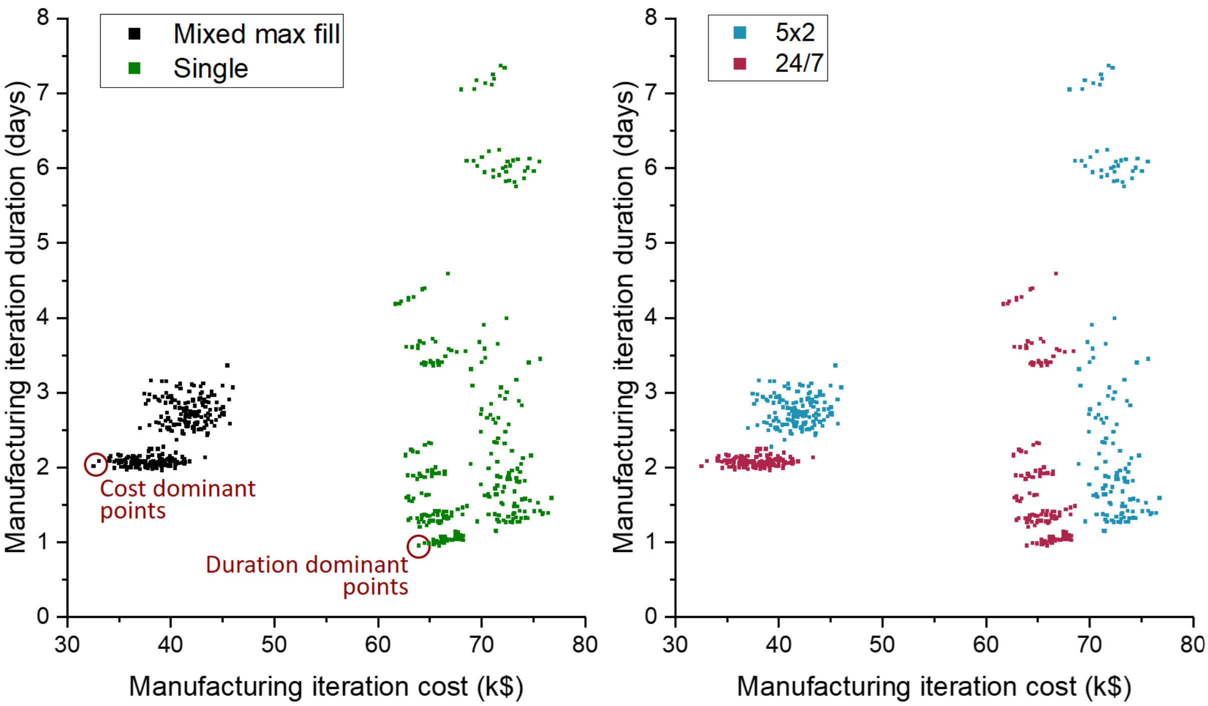


Figure 5.25. A time-cost map of possible configurations of the manufacturing system: (a) segregation of the points by the batching strategy; (b) segregation of the points by the shift mode.

We can see that operating on the three-shift mode is beneficial for both productivity and cost of operations. Going from the mixed max fill batching strategy to the single strategy moves the cost range from 30,000-50,000 USD per iteration to 60,000-80,000 USD. In this case, manufacturing duration can increase and decrease depending on the number of printers in a system. As shown in Figure 5.26, the systems with fewer than three printers for the steel parts and operating on a single strategy for batching

[44] A total simulation runtime is 25.5 hours on one core with 2.90 GHz CPU and 32 GB RAM.

perform several times worse in duration than any configuration operating on the mixed max fill strategy. However, if the number of steel printers reaches three or more, then the single strategy has an equal or outpacing productivity than the mixed max fill strategy. Conversely, it seems irrational to use more than one printer of each type if the facility follows the mixed max fill strategy. Finally, Figure 5.27 shows that the layout parameters used in this study turned out to not influence the results in any noticeable pattern. Taken in total, the cost-dominant points (Figure 5.25) are represented by the configurations with one printer for each material, mixed max fill batching strategy, and the 24/7 shift mode. The duration-dominant systems are those with seven printers for the steel parts, five printers for the titanium parts, and operating on a single strategy 24/7.

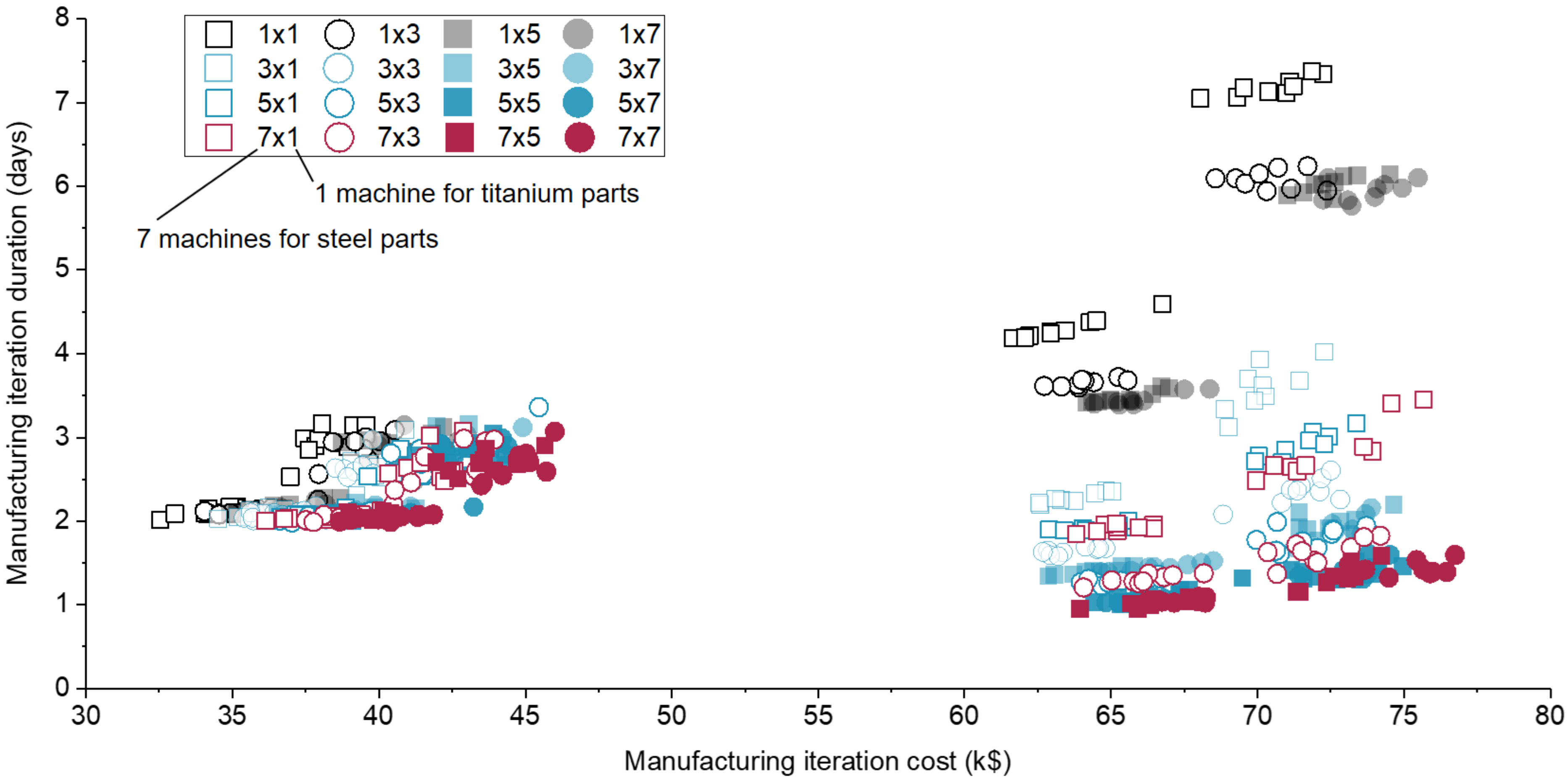


Figure 5.26. A time-cost map of possible configurations of the manufacturing system categorized by the number of printers in a system. A "7x1" configuration means that the system has seven machines for printing the steel parts and one machine for the titanium parts.

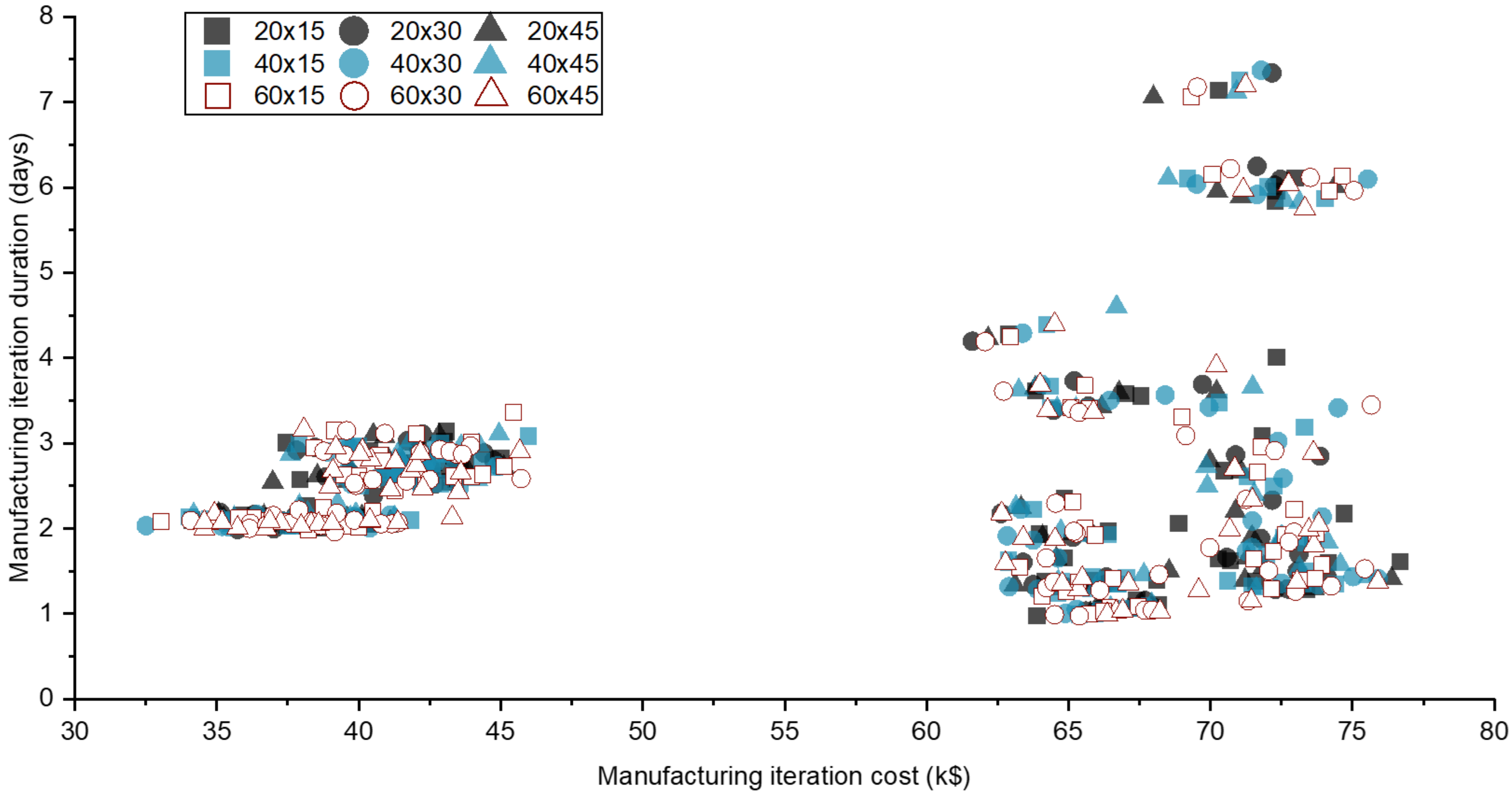


Figure 5.27. A time-cost map of possible configurations of the manufacturing system categorized by the layout parameters. A "60x15" configuration designates the system with 60 meters limit for the division width and 15 meters limit for the division length.

5.10 Summary of the recommendations on conducting the ICM process on the pylon

While working on a large multidisciplinary project, the teams of different years have faced various reasons for conducting the engineering changes that were mostly emergent, i.e., error correction, change of function, safety insurance, or quality assurance. Since in most cases these reasons will affect – directly or indirectly – both engineering and manufacturing domains, integrated analysis is necessary to provide an accurate quantitative assessment of the possible repercussions. In studies ##1-7, we go through a set of demonstrative analytical use cases that show how we can use the developed framework when planning and implementing the change scenario illustrated in Figure 5.4. As a result, they provide an integrated evaluation of the techno-economic performance, both in PD and manufacturing domains, which can be summarized with the following list of recommendations:

1. Various engineering changes on the pylon can be numerically characterized through a set of retrospective indicators (Figure 5.9). They can include the change propagation, i.e., the number of components involved in a change, people involved, collaboration resistance, people reappearance in a change, and component's overall change count. These metrics synthesize the complexity of a design process and reflect the amount of effort necessary to implement the change triggered by a given component. By running a set of simulations, we create a map of the lead time distributions for all components (Figure 5.10), which compares different originations of the changes and thus guides the team in project planning. Using only this analysis without detailed consideration of the manufacturing activities, we can assume that the given change scenario will take five to thirteen days, depending on the need to redesign a firewall subsystem. Having such an estimate in a given schedule context, the team can decide on the scale of the change they are planning to introduce to have higher chances of finishing the whole project in time.
2. To investigate the process structure, we can run a series of experiments varying the durations and rework probabilities of the constituent activities. As a result, we can compare different process dynamics through an integrated simulation, accounting for both engineering and manufacturing operations costs and times. We can see that to stay in the specified timeline and the budget limit, the default parameters of the ICM process can be increased only in terms of the duration of the PD steps by a factor of 1.4 maximum, when the iteration probabilities are reduced five times. The rework probabilities cannot be increased as this will lead to a budget overrun. The analysis has also shown that the financial limits for PD and manufacturing activities in different process configurations are between 3,200-33,900 USD and 37,500-64,300 USD, correspondingly.
3. The addition of the design for AM (DfAM) activity is expected to reduce the project costs. By simulating the two process architectures, the framework has shown that the AM technologist's

involvement can decrease the manufacturing and total expenditures by 27% and 9%, respectively. However, in the current setting, adding the DfAM step is expected to prolong the change, on average, by 20%.

4. Further, the analysis of a single manufacturing process parameter – the unrecyclable fraction of powder – has shown its multifaceted impact on the whole product creation system. The decrease from the original 9.5% to hypothetical 0.5% waste rate can lower the cost of one production iteration by 22% and the total change management cost by 15%. In this case, the project manager needs to consider the possibility of implementing the solutions improving powder utilization if an average saving of 15,000 USD per change will justify their cost (Figure 5.21). Another benefit to consider is the opportunity to broaden the flexibility in process structuring, allowing for an additional 40% increase both in rework probabilities and PD tasks' durations (Figure 5.22).
5. Studies ##5-6 show that the change in part mass of the components will have a significant impact on the manufacturing duration and cost. Producing the parts with the masses twice that in the original design would increase both the manufacturing total costs and the manufacturing total duration by 70%. Increasing the mass of supports, on the other hand, is expected to make a much lesser impact: 13% increase in the manufacturing total costs and the manufacturing total duration. These tendencies observed in studies ##5-6 seem to linearly correlate with the variable parameters of the studies, i.e., part mass and support to part mass ratio. From this analysis, we can infer that the team can consider a wider range of the design change options introducing additional support structures and not varying the component mass significantly. However, a more thorough investigation of the consequences for the post-processing operations might be necessary.
6. The configuration of the AM-enabled manufacturing system plays a vital role in the project schedule and cost. Depending on the circumstances, the team is suggested to select one of the two options: the first uses the mixed max fill batching strategy and has one machine for each material type, whereas the second works on the single strategy and includes seven machines for the steel parts and five machines for the titanium parts. These configurations both operate on the 24/7 shift mode and are expected to provide the least expensive and the shortest options, correspondingly.

Each of these studies should not be viewed as the way to find a universal solution for any change case involving the pylon. The tradeoffs produced by the framework need to be used as the supporting quantitative maps that facilitate the planning of the upcoming PD and manufacturing operations. The selection of the best option should consider the current context of the change, specifying the availability and the cost rates of the organizational resources, i.e., people, the manufacturing resources, i.e., equipment and shop floor workers, as well as the particular change constraints, such as the budget and the schedule.

Chapter 6

Discussion and Conclusions

This chapter summarizes the work presented in this thesis and provides the conclusion on the developed solution. It discusses the current limitations in applying the presented framework, suggests ways to overcome them, and proposes further research avenues.

6.1 Summary of the thesis

The motivation of this work is to promote the importance of studies at the intersection of engineering and manufacturing domains by advancing the capabilities of combined analysis. To achieve that, Chapter 2 starts with the literature review on the nature of the product creation process and the dominant technologies that transform it. This resulted in the identification of the research gaps related to efficient handling of engineering and manufacturing changes (EC and MC) and the influence of additive manufacturing (AM) technology. These findings have significantly narrowed the research focus, creating a specific niche to be filled by this dissertation.

Addressing the research question, Chapter 3 elaborates the context of a problem to set the stage for a specific solution closing the gaps. It elaborates the concept of integrated change management (ICM) by formulating its definition and detailing the reference process for such an approach. It shows the critical connections between the domains and the involvement of the major stakeholders in ICM. Chapter 3 proceeds with the investigation of AM impact, which builds on the interview-based case study conducted with a large energy sector manufacturer adopting serial LPBF-based production of metal end-use components. Based on these parts, the chapter concludes with particular implications of AM introduction to ICM. One crucial inference is that the need for the ICM concept, which is initially elaborated in a general context, is getting more critical in the AM context; at the same time, AM needs ICM for better coordination during technology deployment and use. The closure of the discovered gap requires a comprehensive viewpoint that can consider multiple aspects of ICM and AM and provide a reliable quantitative assessment of the necessary cost and time KPIs.

Chapter 4 takes the call and proposes the solution. It first examines the existing methods of analyzing the product development (PD) and production operations. After comparing various modeling approaches, the thesis presents a new method that combines the existing techniques' strengths and enables the required integrated analysis. It comes from two distinct solutions implemented for PD and manufacturing simulation. After proving the efficacy of each method in respective domains, this work merges them into a combined analytical framework suitable for analysis of ICM operations in the AM context.

Finally, Chapter 5 demonstrates the solution's application in a realistic environment based on the aerospace project. It executes the series of studies observing the influence of the process architecture and manufacturing parameters on the product creation system as a whole. It outputs a comprehensive summary revealing the quantitative implications of specific engineering and production planning decisions. The study enabled by the framework illustrates that even one compound manufacturing parameter – that reflects powder recyclability – can have a far-reaching effect on the agility of the ICM process and measures it. The use case shows the importance of the combined analysis by evaluating the inter-domain impacts and illuminating the tradeoffs between the change cost and lead time.

6.2 Discussing the utility of the ICM concept and the developed modeling framework

By elaborating on the integrated change management (ICM) concept, this work aims to advance collaboration across the engineering and manufacturing domains. It believes that better coordination in handling the changes can minimize rework and thus reduce their high costs. To reach that, it is imperative to perceive and accept the ICM paradigm both by the actors of these two fields and the management organizing the process. The use case in Chapter 5 emphasizes how inseparable are the design and production planning decisions and how influential their consequences for each other.

However, to uptake the ICM approach, the company must go through an organizational change. It needs to adapt the existing business processes by bringing together the ECM and MCM routines and establishing a set of new coherent workflows. Moreover, as discussed in section 3.1, the degree of inter-domain integration is expected to depend on the application. Therefore, the company also needs to provide a guideline on executing the ICM process in a particular context. Additionally, this is related to the computational cost of running an integrated analysis instead of the domain-specific review. It may require more time to comprehensively evaluate the change request data and develop the corresponding change concepts. As shown in Chapter 5, the studies with multiple configuration parameters can take several dozen hours because of the granularity of the framework's manufacturing module. Coping with this requires powerful workstations supporting the distributed simulation option that can reduce the simulation runtime severalfold. Nevertheless, given an ongoing increase in computing performance (Theis and Wong, 2017) – and the corresponding devaluation of the computational cost – this work does not expect the data processing aspect to be a considerable challenge in adopting the ICM practice.

To further support the practitioners embracing the ICM paradigm, this dissertation fulfills the need for specifically designed analytical instruments. The presented integrated modeling framework captures the activities at all PD stages, going from the change identification and planning to its manufacturing implementation. It allows to model the operations in PD and AM-based facilities with high granularity and within a single environment. Having a channel for configurated input of the case-specific decisions related to the product design, manufacturing system structure, and planning of the product development and manufacturing processes, the framework allows making a compound assessment of a custom product creation system. It supplies the change board with quantitative estimations on the change lead time and its standard deviation, thus indicating the reliability and robustness of the particular ICM process. The framework also outputs a detailed cost breakdown for the production side. Applying this tool, the company can enhance its performance analytics with reduced uncertainty and thus enable a more rigorous search of prospective improvement avenues.

Given the complexity of an ICM process created by stakeholders' convoluted interactions and tasks' iterations, such a configurable framework would be useful for architecting the process, the manufacturing system, and further resource planning. Additionally, the framework aids project navigation by accounting for the uncertainty and iterative nature of PD operations. These capabilities are expected to improve the planning and scheduling of the change projects, as they inform on the effort requirements for various options. Having the numerical evaluations for the necessary cases, the organization can minimize the opportunity cost by improving the allocation of its resources. Putting it in simple terms, the company can assess multiple change scenarios and select a combination of those that result in minimal time and cost expenditures.

Based on a realistic use case of the framework during the redesign of an aircraft pylon, studies ##1-7 in Chapter 5 examine a generic change scenario to grasp a larger set of cases and facilitate the reader's comprehensibility. However, the framework input data structure allows us to define a more specific or intricate case in which the same parameters vary differently for similar objects, i.e., for components of the system undergoing the change or manufacturing resources, e.g., printers. For example, it can have different values for the changes in masses of diverse parts or consider specific production planning decisions, such as a change in the productivity of one machine type or selecting the manufacturing scenario depending on the design change. Suchlike cases require a thorough definition of the experiments' input data and variables to fully reflect a study of interest.

Moreover, though this work's focus is integrated change management, the insights on engineering and manufacturing interconnection and the framework application can be extrapolated to generic PD and production operations. By going beyond ICM and formalizing a reference process – such as shown in Figure 4.3 – based on the entire PD scope discussed in Figure 3.8 and elaboration of manufacturing operations management by the production department, we can apply this dissertation's approach to study a complete product creation workflow quantitatively. In doing so, the framework would also need to account more thoroughly for cooperation with the suppliers and distribution of manufacturing operations among several facilities. Then, the use of a proposed approach would serve as a powerful extension of research on PD operations discussed at the beginning of section 4.1. A detailed view of the production operations would significantly reduce the uncertainty and inaccuracy coming from quantitative assessment of the manufacturing domain. Thus, an uncommon value would come exactly from the emergent function of the developed system: an integrated, comprehensive evaluation of the design, engineering, and manufacturing activities' costs and durations, combining the product, process, and organization viewpoints.

Such capability is crucial for facilitating AM industrialization as it supports researchers and practitioners in finding its cost-efficient applications. The framework allows comparing different architectures of the product development and manufacturing systems in terms of various time and cost metrics. As a result, it enables the search for more rapid and economically viable product creation practice – balancing between the process agility, reliability, and robustness – in a given context, considering major decisions on planning the design, engineering, and manufacturing operations.

However, along with these advantages and an expected practical utility of the proposed solution, there are several limitations associated with its current implementation. The next subsection discusses these limitations, points at the challenges of conducting an analysis presented in this thesis in the future, and proposes ways to overcome them.

6.3 Discussing the current limitations and challenges

First of all, there is an overall challenge of establishing one universal integrated change management (ICM) procedure because of its dependence on a context. As discussed in section 3.1, a specific process architecture needs to be established according to the conditions suitable for a particular company or case. This implies a difference in ICM process constituents, i.e., activities, and the requirements on degrees of integration between engineering and manufacturing domains. On the other hand, the proposed framework does account for the need for such adaptability by providing an ability to specify the process structure and iterations between its steps via rework probabilities, impacts, and learning factors.

Secondly, this work recognizes itself as limited in discussing the data structure and infrastructure necessary to implement a proposed ICM practice. In connecting the engineering and manufacturing areas, it is essential to bridge all data processing instruments involved in product lifecycle management and thus enable an environment facilitating the product development (PD) process (Gagné and Fortin, 2007). An efficient system shall possess a complete digital suite and a proper architecture for unimpeded transfer and data processing across the participating domains. Moreover, since the ECM and MCM processes, in many cases, are a cross-company effort, an integrated solution to information management must provide the means to minimize data translation when it is passing the company borders (Wasmer, Staub and Vroom, 2011). Though the variety of supporting software applications demonstrate some degree of commonality, they still lack unification for unobstructed integrated analysis (Morris *et al.*, 2016). By providing a necessary architecture and establishing the interfaces to the presented framework, the data collection process and the techno-economic evaluation presented in Chapter 4-Chapter 5 can be streamlined and promoted to a continuous analytical routine.

Thirdly, with respect to the modeling framework, future research should address several aspects related to the breadth of its applicability. One is connected to consideration of the concurrent activities within the ICM process. In general, the overlapped PD steps influence the process's iteration intensity by inducing uncertainty and thus causing rework (Wynn, Grebici and Clarkson, 2011). These concerns are critical in finding the process architectures optimal in project duration and cost, as discussed by Krishnan, Eppinger, and Whitney (1997), Lin *et al.* (2009), Meier *et al.* (2015). Being a part of an entire PD project, the ICM process inherits the same nature, including concurrency. Therefore, this aspect requires adequate attention in the simulation-based analysis, especially if the approach will be applied not only at the change level but will investigate an entire PD process. In the presented framework, this concern has been addressed via the chosen retrospective indicators that condense the complexity of the design process and embed the concurrency influence in the indicator refining activities' durations (see section 4.1.3). At the same time, the quantitative effect of task parallelization can also be considered through the specific modeling rules, such as by Cho and Eppinger (2005). However, in the application to the ECM-like process, which can be perceived as a sub-project within a PD project, the simulation of concurrency might lead to excessive modeling complexity and impede the approach's applicability. Thus, this work sees a tradeoff challenge between the modeling granularity and the practical utility of the method. Therefore, the chosen approach should first be reviewed for its operational usefulness in dynamic and agile PD environments that industries need these days.

In connection to this challenge, the framework is limited in simulating the study of multiple decision alternatives simultaneously, i.e., imitating the set-based concurrent engineering (SBCE) practice. Instead of iterating on one engineering solution at a time as in point-based approaches, SBCE tries to capture a clear picture of all possibilities by starting with the broad definition of domain-specific solution sets (e.g., in design, manufacturing, testing, or customization domains), and then intersecting and narrowing them until they will converge to a single feasible solution (Sobek II, Ward and Liker, Jeffrey, 1999). As Langmaak *et al.* (2013) note, the factory cost models can enable the sensitivity analysis, illustrating the influence of various cost drivers and aiding in implementation of the SBCE principles. However, this limitation is rooted in a general scarcity of work on SBCE, or set-based design (SBD), beyond the conceptual stage. The studies of SBD paradigm in such contexts as design knowledge reuse, PD process frontloading, and prototyping and testing are necessary for closing the gap (Toche, Pellerin and Fortin, 2020). In fact, it is possible that the stagnation in this part of research – both in academia and industry – is caused by the high prototyping expenses within the conventional manufacturing paradigm and that the AM-driven facilitation of multi-alternative studies can advance the field. To extend the application of the presented framework to the analysis of an SBCE practice, it is necessary to complement it with an ability to simulate and evaluate multiple decision alternatives in parallel along the steps of the process of study. Such an analytical capability might support the development of SBCE.

Another aspect in which the framework's application can face difficulty is collecting a high volume of quantitative data on past changes proposed in section 4.1.3. Since the companies differ in the extent they track and store the details of change data, and given that the proposed granularity reaches the activity-specific metrics, it might be necessary to establish a more thorough data collection procedure to apply the approach. One way is to bring exhaustive digitalization of the processes that generate and process data; e.g., a firm can rely on the PLM and ERP infrastructures to rigorously keep and organize the change information. Yet, it would still require appropriate formal procedures supporting data collection and management. Otherwise, the accuracy of parameter refinement can be deteriorated. Moreover, if the framework will be embedded into the PLM system, an integrated PD and manufacturing modeling can benefit from a more detailed consideration of the requested changes. This way, it could analytically evaluate the manufacturing implications of the engineering changes, and vice versa.

Further, despite the method's granularity in many aspects, it is still limited in the accurate definition of distinct modeling assumptions influencing predictions' quality. With respect to the simulation of PD operations, the somewhat simplified scaling rules represented in equations (1)-(8) (pp. 85-87) can be revised and complemented with more strict company-specific assumptions and with more meticulous estimation techniques, as in (Bashir, 2000). For example, the characterization of the learning curve parameters could account for the experience of the design team and its variable impact on different process tasks. Similarly, certain assumptions on manufacturing operations are abstracted to simplistic terms, e.g., when calculating build time or gas consumption based on the volumetric constants. For instance, in study #6 the framework considers the details of post-processing operations with a linear relationship between the volume of supports and their removal time. Yet, in reality, post-processing can be tricky and involve several processes of different nature, e.g., mechanical or chemical, which will take an amount of time commensurate to or exceeding that of printing. Therefore, more granular assumptions are necessary to accurately investigate the questions of surface finishing and supports removal, such as in study #6. On the other hand, there are new support-free printing technologies appear, which attempt to significantly reduce the post-processing effort (*Velo3D SupportFree Process - VELO3D*, 2020). A revised version of the framework needs to account for these advances as well. To that end, this work sees integration with specialized external simulators or estimators enabling greater accuracy and configurability.

Also, the scope of this study was restricted in the search for optimal solutions. For example, Chapter 5 compares a range of combinatorically-produced system configurations in time- and cost-based metrics. However, such a comparison cannot guarantee the identification of the global optimum. The proposed framework rather sets the stage for optimization task formulation by bringing together various system parameters and enhancing the understanding of their individual and combined impact. It also can serve as the follow-up simulation-based validation of the optimal parameters set. A possible optimization study can be devoted to configuring the manufacturing system for maximum productivity, e.g., by defining the machines' specifications. Another objective might be determining the optimal parallelism and concurrency between the PD steps – as discussed by Eversheim and Schulten (1999) – for the minimum change duration. The simulation-based validation of such a study would require the framework functionality of modeling the concurrent activities similarly to Cho and Eppinger (2005).

Another current limitation of this work stems from the difficulty of conducting a physical validation of the developed modeling framework. Through the realistic use case presented in Chapter 5, this work validates the framework's functionality in integrated modeling of the product creation activities but not the accuracy of the modeling rules and involved qualitative and quantitative assumptions. The latter requires a physical validation through a real case study to compare the simulation-based evaluations with the results of hands-on experiments. Therefore, the demonstrated use case is considered to validate the knowledge contribution but not the contribution to practice (Isaksson *et al.*, 2020). Presumably, such validation needs to go under an industrial partnership and through the following four stages:

1. Case study data collection to define the necessary input parameters related to:
    a) Characterization of the ICM reference process with respect to the constituent activities, their durations, iteration probabilities and impacts, and learning curve factors (see Figure 4.4 and Figure 4.5).
    b) Calculation of the retrospective indicators based on the historical data (see Table 5.2).
    c) Parts catalog definition according to Table 4.1.
    d) Machines specification according to Table 4.2.
2. Revision and refinement of the modeling rules and assumptions discussed in sections 4.1-4.3 and appendix A5.
3. Definition of the studies – such as those described in Chapter 5 – to be simulated by the framework and executed physically.
4. Comparison of the data collected from the physical and simulation-based experiments devoted to the same studies.

In looking for such case study, this work seeks access to a metal LPBF-enabled product creation system. The validation also requires a sufficient immersion into the project that includes the studies of different PD or ICM reference process architectures. To examine the manufacturing part of the framework, the case study shall investigate different system configurations and operation scenarios. Such a demanding environment represents a significant challenge for validating the digital instruments optimizing the manufacturing system, especially if run solely in an academic setting. In addressing this, future research can approach the PD and manufacturing domains independently for validation of the respective framework modules and then conduct a complete study in a holistic environment. However, it is still challenging to verify and validate the accuracy of the taken activity-based costing approach, given that the other estimation techniques tend to aggregate the costs and lack a commensurable granularity (Spedding and Sun, 1999).

Moreover, along with validation of the modeling framework, it is necessary to prove the benefit of the elaborated integrated change management concept. In this work, the objective of engineering-manufacturing integration was formulated based on the evidence found in the literature. Now, having the ICM concept defined and its reference process elaborated, it is necessary to validate the asserted value of cross-domain integration. One possible way to do this is to conduct a comparative two-stage study involving both engineering and manufacturing changes (EC and MC). At the first stage, the task will be performed by managing the EC and MC separately. At the second stage, the engineering and manufacturing teams would be encouraged to collaborate along the ICM process, especially during the phases highlighted with Figure 3.7. Upon completion, it would be possible to compare the total change effort and assess the anticipated coordination improvement. However, in such a study, it might be challenging to provide the same initial conditions at the first and second stages with regard to the novelty of the task or the team experience. If these stages involve the same engineering and manufacturing teams, then, likely, at the beginning of the second stage, the engineers would have more knowledge about the change than at the beginning of the first stage. If the study would employ different teams for the first and second stages, then the challenge is to assemble the teams with equivalent experience. Both scenarios might impede an accurate evaluation of integration influence in terms of, e.g., change lead time and cost.

Speaking of practical validation, it is important to underline that the dissertation investigates the AM-based environment particularly. Nevertheless, the presented ICM conception and the proposed framework architecture can be applied in the conventional paradigm, i.e., when the subtractive and formative manufacturing techniques are employed. To cover it, the framework shall include the object libraries and account for the related assumptions not only for AM workflow but for the other necessary operations, e.g., turning, milling, or stamping. With this functionality, the proposed approach can explore a broader scope of product creation options, producing a quantitative comparison in costs and times of processes that include and do not printing. Also, adding such functionality would allow comparing the techno-economic efficiency of the ICM procedure in conventional and additive contexts and, potentially, expose the additional benefit of AM. Such studies are critical in searching for cost-effective AM applications at various scales, leading to technology adoption and field advancement.

Furthermore, the AM context of this work was also limited. The interview-based study reported in section 3.2 has been conducted with only one manufacturer in the energy sector and has been devoted only to one specific AM process. Therefore, this work cannot claim the generality of the findings related to the transformation of the product creation process discussed in section 3.2.2 and their transferability to other industrial settings. To overcome this limitation, it is necessary to conduct similar studies – following the same method of interviewing, data collection, and processing (section 3.2.1) – with the companies working in other industrial sectors (e.g., automotive and medical) and using other metal-based AM processes with high industrialization potential, such as electron beam melting, binder jetting, or direct energy deposition. Moreover, a complete AM context must consider research devoted to other non-metal materials. Having several cross-industry studies that review a full spectrum of AM technologies, e.g., listed in Table 2.1, would allow synthesizing more generalized and transferrable insights on AM impact.

Another contextual limitation concerns the applicability of the proposed modeling approach in different industrial sectors. Chapter 5 shows the value of the developed framework on one aerospace example. Using the method described in Chapter 4, it was possible to simulate and analyze the case-specific PD and manufacturing domains in integration. However, the industries, or even companies within the same industry, may differ in how they organize the product development process, distribute the roles, and configure and control their production systems. Hence, the framework must be tested subject to the variation in practices that companies use for developing and manufacturing automotive, medical, aerospace, and other industry-specific products. Since the current approach implementation illustrated in Figure 4.19 allows to specify the particular architectures of the product development and manufacturing systems, it is expected to be applicable to other discrete production contexts. Still, the robustness of the simulation results and method sensitivity to the industrial context need to be proven through additional case studies. Thus, a more profound claim of contribution to knowledge and practice demands a series of studies in various manufacturing sectors.

With respect to benchmarking of decision alternatives, this thesis might also be limited in application to various comparison scenarios. This work uses two primary KPIs: change lead time and cost. Though these metrics considered to be first-order for a company's market competitiveness (section 2.1), the other indicators might be preferable in a certain context. For example, a company can pursue various sustainability objectives coping with numerous environmental problems highlighted and addressed by various international initiatives. They can relate to the resource consumption and environmental impact issues, such as water scarcity, water quality, atmospheric CO_2 concentration, ecosystem eutrophication, air pollution, or others (Chandrakumar and McLaren, 2018). Also, the thesis did not discuss the "make or buy" decision-making process. It is an essential aspect affecting the company's ability to control the design and manufacturing operations and achieve the defined strategic objectives. Therefore, a systemic study with more evaluation dimensions is necessary to assess the global impact of AM and ICM.

Adding to that, this work did not consider the introduction of the other new technologies revolutionizing the shop floor operations. Since the advances in processes virtualization and automation, data traceability, or energy management influence the cost, rate, quality, and flexibility of the system (Frank, Dalenogare and Ayala, 2019), their individual or compound impact also requires a quantitative evaluation. Such analysis by the proposed framework demands a further population of the model libraries with technology-specific elements. That is, the framework needs more diverse modularity enabling the construction of custom system configurations for given research applications, in addition to the presented modules for the analysis of the additive manufacturing context.

Finally, a low level of user-friendliness of the proposed modeling framework is another issue to address in future work. To facilitate the adoption of the approach, it is necessary to minimize user effort in setting up a case-specific study and in analyzing the output data. Currently, the framework requires manual input of multiple parameters in its different modules (see Figure 4.19) and manual post-processing of the simulation results into tradeoff charts presented in Chapter 5. The automation of these steps – e.g., through integration with the PLM and ERP infrastructures for input data collection and with special modules for results analysis – would expedite the process and, most likely, considerably improve the user experience. In turn, these advancements would aid in the industrialization of the approach and extraction of its commercialization value.

The author views these considerations as vital to address in future work for better practical applicability of the proposed ideas and framework. It is essential to emphasize that all these concerns do not devalue this work's contribution but only expose the complexity of the topic and point at the critical research items. The presented discussion of the ICM concept, AM context, and the integrated modeling framework thus serve as the basis to support the subsequent development of the topic. This work sees in itself the potential to stimulate the related research paths in product development and manufacturing. Section 6.4 proposes the concept of a process twin relying on the presented modeling framework, and section 6.5 provides an outlook for three other distinct research directions.

6.4 Proposal of the Process Twin concept for product development operations

In section 1.1, this work points at the novel capabilities promised by implementation of a digital twin (DT) concept: a detailed virtual representation of a physical system, i.e., product, that has an automatic and bidirectional continuous data exchange with it and operates throughout its whole lifecycle (Trauer *et al.*, 2020). Going further, this work suggests that building on research in product development (PD) modeling and simulation, the DTs can also be used to analyze the systems at the intersection of process and organizational domains. Particularly, it sees the value in employing such fundamental instruments as the Design Structure Matrix (DSM) from systems engineering theory, and comprehensive simulation methods, such as Discrete-Event Simulation (DES), for modeling the PD operations in their as-designed state (Browning and Eppinger, 2002; Maier *et al.*, 2014; Eckert *et al.*, 2017; Wynn and Clarkson, 2018). Then, using the historical information on past as-executed processes and tracking the ongoing changes, these models can be promoted to "*Process Twins*": the models of company-specific workflows that regularly refine the as-designed digital representations with the real data on system behavior (Shakirov *et al.*, 2021).

Process twins could augment business process analytics with continuous quantitative assessment and planning of the workflows with harmonized reliability, i.e., total PD duration variability, and robustness, i.e., PD duration's sensitivity to rework probability (Yassine, Whitney and Zambito, 2001). This way, they would facilitate continuous analysis and improve engineering management operations in firms (Trauer *et al.*, 2020).

However, to enable this, we need to learn how to represent the involved physical and virtual entities, the environments, the states, and the other major characteristics listed for product DTs by Jones *et al.* (2020) for the DTs in the organization domain. Moreover, great attention must be paid to epistemic and aleatory uncertainties intrinsic to engineering processes, which complicate the estimation of the time and cost metrics (Pahl *et al.*, 2007; Wynn, Grebici and Clarkson, 2011; Hamraz, Caldwell and Clarkson, 2012; Yang *et al.*, 2014). Thus, a correct characterization of the DTs is a prerequisite for approaching the challenges associated with data collection, modeling, and analysis in the organizational domain. To close this gap, we first shall leverage the methods of reproducing and analyzing the PD operations such as those described by Browning, Fricke, and Negele (2006), Karniel and Reich (2009, Wynn and Clarkson (2018), and discussed in section 4.1.

Further, it is necessary to connect them with the planning and management software solutions governing the PD projects and changes in particular. By building the direct connection with the product lifecycle management (PLM), enterprise resource planning (ERP), configuration management (CM), manufacturing process management (MPM), and other standardized digital PD management platforms (Gagné and Fortin, 2007), the framework can benefit from the richness of data necessary for its retrospective analysis. Certainly, such integration would require a clear information processing procedure for reliable characterization of the PD data. For example, in integrated change management (ICM), collecting information on the ongoing integrated change (IC) project would enrich the system with past data for future evaluations. For the ongoing ICM project, such integrated infrastructure would allow to refine the simulation results with the real process data. As shown in the ICM process twin concept (Figure 6.1), the modeling and evaluation module (C) should be connected to the database of past changes and retrospective indicators (B) that is tracked by a chosen set of data management systems (A). Module (C) then produces the relevant performance evaluations (D), which the PD team is then using to review the ICM process, aiming at the more efficient structure and parameters of the reference processes.

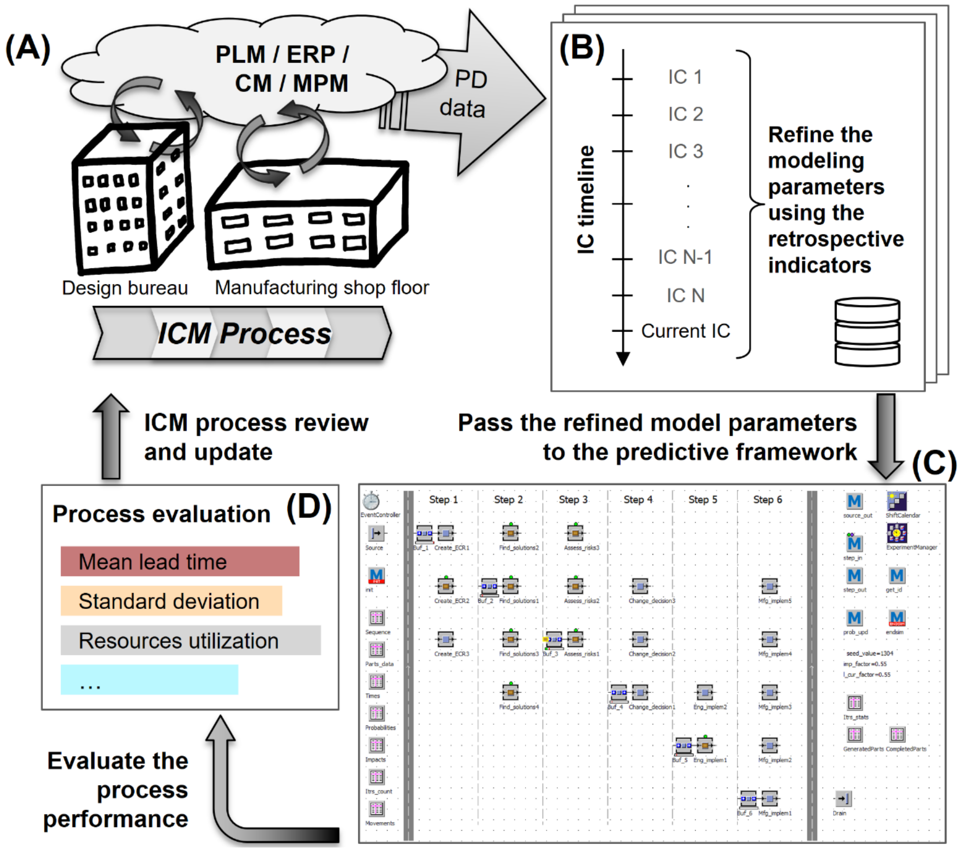


Figure 6.1. ICM process twin concept.

Following the proposed concept of operations, the PD team can activate tacit knowledge hidden in the history of past ICs and facilitate the continuous improvement of its operations. Thus, a company can become a true *"learning organization,"* in which *"a better way is always welcome, and there is a clear and quick mechanism for changing a process, which then becomes the new hypothesis for the best way to do the work"* (Browning, Fricke and Negele, 2006). Also, by automating the learning process through such a digitalized routine, the organization can overcome the associated knowledge extraction difficulties, such as workers' lack of willingness to learn from mistakes mentioned by Schindler and Eppler (2003). Reciprocally, the process twin of the PD system is expected to become more precise due to the growth of the historical dataset used in the refinement of the simulation parameters.

However, there is also a challenge of ensuring cyber-security for all parties of the project. Since the DT development demands a deep, multidisciplinary, and fast-paced cooperation for data update – and therefore involves open and shared data – it should be protected from inappropriate use and external threats (Huang *et al.*, 2020).

6.5 Other avenues for future research

6.5.1 Towards a universal configurable framework for factory simulation

The first research path focuses on the development of factory simulation capabilities. The approach presented herein uses the commercial instrument to provide a framework, which can instantaneously model a necessary LPBF-based production process that follows a prescribed workflow. For this, it uses a set of the developed methods that derive a specified system's configuration and govern the logic of all distinct process elements (e.g., preparation of the STL file, printing, or build plate removal). As a result, these workflow steps are represented by the modules that consist of the processing object (e.g., a printer), a set of auxiliary system elements (e.g., the input and output buffers), and the collection of methods required for sufficient definition of the object's behavior (e.g., calculation of the printing time).

Based on such architecture, this approach can enable modeling of various process chains that are based on the other manufacturing operations of additive, subtractive, and formative nature. Similarly to LPBF modeling, a given manufacturing technique can be segregated into respective generic stages executing raw material's transformation into the parts and assemblies. Therefore, a comprehensive modular approach would require the corresponding sets of tunable objects and methods for each stage of various processes, which will receive the input data (e.g., the material specification or processing regimes), and output the operation result along with the information on resources expended. By combining the libraries' elements, we can simulate facilities designed to process a selected combination of materials, with both dedicated and shared equipment and labor.

Further, for instance, we can use the model to recommend which machines – varying by the technology and size – to employ and which batching strategy to follow to achieve the target quality, lead time, and system performance. The hypothesis is that this will be instrumental to flexible, digital "service bureaus," for instance, combining various AM and traditional methods to enable on-demand production from a catalog of digital data, including CAD files, workflow instructions, and machine toolpaths. Given the breadth of existing manufacturing techniques, their ongoing transformation by innovative technologies, the appearance of the novel production methods, and relative complexity of process definition (see the example of LPBF process characterization in section 4.2), the population of the model libraries in such a framework shall happen gradually. One way to grow it is through case studies or other specialized research efforts supplied in an open-source manner.

Moreover, to provide accuracy in operations temporal evaluation, such a framework shall have the interfaces for data exchange with external estimators. In (Shakirov *et al.*, 2020), this work demonstrates such capability on the example of printing time assessment. To set the process duration, the model shares the build characteristics through the local client-server connection, i.e., the socket communication, with the estimator encoded in a Python script and receives the calculated printing time[45]. This approach enhances the framework's modularity and outsources its functions involving costly computations, thus retaining its flexibility while maintaining a high estimation accuracy.

As a result, such a toolset can radically expedite the accurate modeling of an arbitrary manufacturing system architecture. Therefore, it has the potential to empower the researchers and practitioners with a comprehensive tool that quantitatively compares different manufacturing system variants in terms of time- and cost-based characteristics. Such analytics are mandatory in selecting the optimal system configuration when there is a need to consider the process and production planning alternatives. In turn, this constructive and model-based approach would facilitate manufacturing research, help explore cost-effective applications, and thus accelerate the adoption of new technologies, such as additive manufacturing.

6.5.2 Defining the scaling laws in an AM-enabled production environment

Going further with the analysis of AM adoption, we can try to quantify the technology performance prospects. Being inspired by Moore's law governing the semiconductor industry for several decades (Moore, 1965; Theis and Wong, 2017), the continuation of this work can aim to derive the "scaling laws[46]" characterizing the evolution of productivity and economic efficiency of an AM-enabled product creation environment. In general, a scaling law shall "manifest a property of a phenomenon of basic importance" (Barenblatt, 2003b). Specifically, using the framework in exploring various production contexts – i.e., with different system configurations and cost rate assumptions – we might observe the natural limitations in the system's cost- and time-based characteristics. For example, assuming the next generation AM machines to markedly drop a nowadays high portion of the capital expenditures in cost per part or volume unit, such as shown in Table 4.13, the other cost elements, e.g., material, labor, or post-processing operations, would become dominant. In this case, we can draw the asymptote for capital costs, implying a rationale for its further cheapening in a given setting: at a certain point, the process improvement would be mainly contingent upon other than, e.g., machine cost factors. For instance, the labor required for support structures removal, as a function of supports volume or degree of process automation, can become the following largest cost-driving factor with its fundamental asymptote limit.

A potential way to investigate this research path is to employ dimensional analysis discussed in (Barenblatt, 2003a). Using it, it is necessary to identify a system of governing parameters characterizing the whole process. This system will consist of two parameters' subsets: the first will have independent

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[45] Credit to Yuri Nikolaev (Skoltech) for implementing the socket connection.

[46] In this work, the use of the "scaling law" term in application to manufacturing modeling and simulation-based analysis is adopted from various research reports of the MIT Mechanosynthesis group under the supervision of Professor A. John Hart.

dimensions, and the second will have dependent dimensions derived from the first. By applying the dimensional analysis in processing the experimental data, it might be possible to produce a set of analytical relationships interconnecting the involved process parameters. In other words, a derivation of the higher-order metrics can ease the navigation in a manufacturing system configuration space and search for a techno-economic balance. This, in turn, can support practitioners in understanding the tradeoff dependencies crucial for AM scale-up.

With such analysis, we can compare the resulting economics of an AM-based process chain to the established manufacturing techniques as machining, casting, and injection molding. What is more, we can study the scenarios with different production scales, target lead times, and applications. Investigating the manufacturing systems as the networks, we can juxtapose diverse production models – such as single-cite centralized facility against a distributed system or a hybrid model – by their techno-economic performance. This asymptotic study can thus direct the harmonized distribution of manufacturing efforts among the employed technologies and geographical locations around the globe.

6.5.3 Understanding the manufacturing workforce transformation

Finally, we see the development of a workforce being another topic closely related to this dissertation. It is an important subject since the efficient transformation of the product creation practice also implies a modified set of skills. It is because the introduction of innovative technologies influences the tasks' content and their distribution among the workers (Autor, Mindell and Reynolds, 2020). Interestingly, even if the majority of company employees recognize and anticipate the upcoming work intellectualization and automation, the transition does not happen until the leadership initiates a thought-out organizational change that includes clear implementation plans (McCreary, Petrick and Zafiroglu, 2019). The major obstacles are related to the consolidated cultural patterns intrinsic to the company and the established business workflows therein. With respect to this work's focus, three specific fields deserve extra attention.

First, in deepening the engineering and manufacturing connection, both sides need to learn the subject of another to improve the empathy necessary in overcoming the integration impediments (Vandevelde, Dierdonck and Clarysse, 2003). The educational and training curriculum shall provide more emphasis on inter-domain connections, such as discussed in section 3.1. For this, the learning process shall rely on and imitate the realistic scenarios with tight collaboration between, e.g., the design and manufacturing engineers. This work believes that the concept of learning factory can become a vital element in workforce development for its embodiment of the "learning by doing" principle (Abele *et al.*, 2017). In (Shakirov *et al.*, 2019), this work discusses a specific scenario and infrastructure requirements that can be used in learning integrated change management.

Another field concerns with the model-based analysis in engineering. Chapter 5 demonstrates the significance of the quantitative evaluation in planning the project budget and timeline. Similarly, the other decisions related to product engineering or process and system organization demand support in accurate numerical estimates. The current digital era can provide it through the ubiquitous use of computational instrumentation in manufacturing and beyond. Therefore, the workers involved at all stages of the product lifecycle need to possess sufficient knowledge in the implementation and use of such tools. It requires a corresponding skillset transformation that will hone workforce capabilities towards the use of digital instruments in addition to conventional physical ones.

The third area of workforce education and training is connected with additive manufacturing. As shows the interview-based case study discussed in section 3.2, a successful introduction of AM requires changes of both technical and managerial nature. It demands new skills in product design and engineering, as well as sufficient organizational and budgetary support from the company leadership. To obtain those, the workforce needs novel educational and training programs focusing on AM and showing the shift in the product development paradigm brought by the technology. Furthermore, the aspect of engineering and manufacturing unification attracts even more attention given the AM's integrity of the design and printing operations.

6.6 The summary of the dissertation's contribution

This dissertation poses and addresses a specific research question: *how to drive a techno-economic improvement of the additive manufacturing-based product creation practice through integrated change management between engineering and production?* Summarizing the whole study presented herein, we can argue that by using the model-based framework – that enables a combined quantitative analysis of the decisions on product design and architecting the processes and organizations in engineering and manufacturing – and at the same time by recognizing, responding, and driving the transformations brought by additive manufacturing (AM), we can minimize the time and cost expenditures on managing the changes and thus advance the product development and production KPIs. To support this vision, this work proposes a concrete contribution with everything discussed and presented in this thesis: a quantitative simulation-based modeling framework for analytical support of an integrated engineering and manufacturing change management practice in the additive manufacturing context. As illustrated in Figure 6.2, it incorporates a set of inputs that this work makes in the adjacent fields:

1. An integrated view on engineering and manufacturing domains through the elaboration of the integrated change management (ICM) concept.
2. A study-based discussion of the transformation brought by additive manufacturing (AM) to the product creation practice in general and ICM specifically.
3. Recognizing the need for comprehensive quantitative analysis of multidomain change planning decisions, the dissertation fulfills it by developing and integrating two modeling frameworks

for engineering and production operations correspondingly. For the former, based on a literature review, this work introduces static and dynamic visions of the product development (PD) operations, leading to the idea of a hybrid modeling approach combining the advantages of both perspectives and to formulation of a Process Twin concept. For the latter, we provide a simulation- and activity-based costing method, which implements the modular architecture for granular and configurable system description, maintaining an extensive modeling complexity. Then, this work demonstrates an integrated modeling approach and validates its capabilities on a realistic use case.

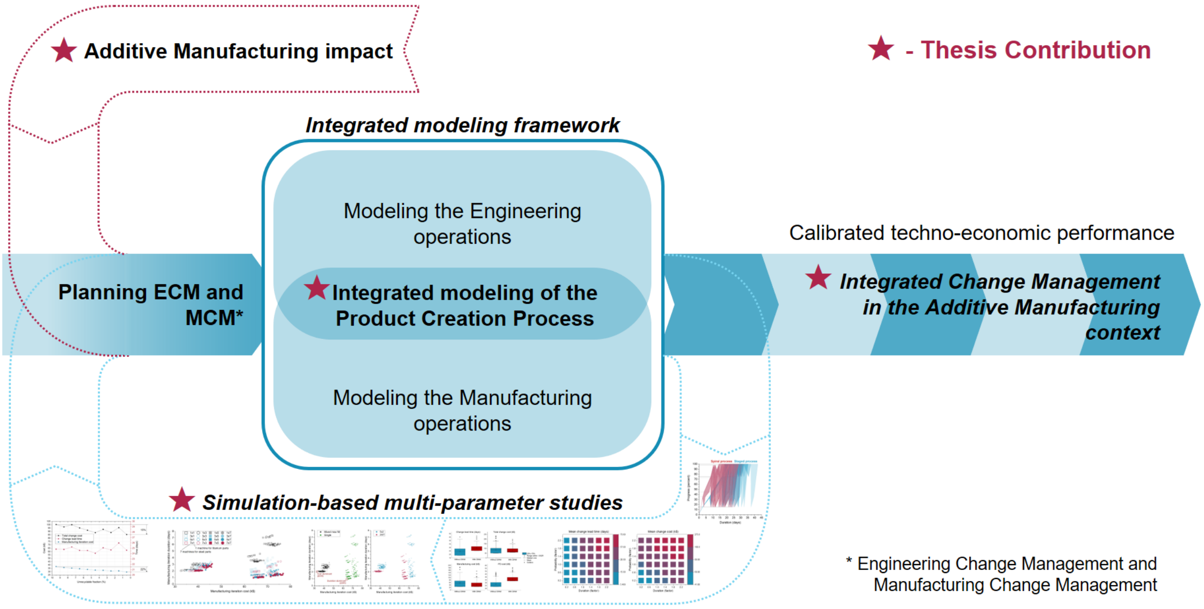

Figure 6.2. The summary of thesis contribution.

In conclusion, the dissertation scrutinizes itself subject to the expected advantages and utility of the ICM concept and the framework, as well as debates the current limitations and challenges. Finally, it proposes the concept of a Process Twin for product development operations, suggests the research directions for its elaboration, and overviews three other distinct research avenues based on the developed solution. They include framework advancement for more extensive configurability and higher accuracy through integration with specialized external estimators, understanding the scaling laws for an AM-enabled production, and the manufacturing workforce transformation.

Table 6.1 gives a succinct summary of the dissertation's contribution – which has been described in detail in Chapter 3-Chapter 6 – by answering the research sub-questions posed in section 2.4. The results of this work have been presented in the corresponding journal and conference publications listed on page V.

Table 6.1. The summary of the findings on research sub-questions posed and addressed by this work.

Research Questions	The findings
RSQ-1.1: What are the critical elements of the ICM notion that its definition shall cover?	The ICM definition shall cover all the ECM and MCM elements related to the product, process, and organization domains, highlighting the emergent potential for coordinated operation across all involved stakeholders.
RSQ-1.2: Which stages shall an ICM reference process have?	The ICM process shall incorporate all stages of ECM and MCM into one coherent workflow, uniting them within the shared timeline.
RSQ-1.3: What are the major interconnections within the network of ICM steps?	The major engineering to manufacturing connection channels within the ICM process are: (1) at its early stage of conceptual analysis, (2) before freezing the EC design, (3) during implementation of the MC.
RSQ-1.4: Which characteristics of the ICM process architecture shall the framework be able to assess quantitatively?	The framework shall have the capability to quantify the reliability and robustness of the chosen ICM process architecture, expressing it in terms of the mean change lead time and its standard deviation.
RSQ-1.5: What kind of methods and tools shall comprise the framework to enable the assessment of the necessary architecture characteristics?	The framework shall rely on the methods and tools enabling the definition of the case-specific data and a process architecture with its further modeling and simulation in time.
RSQ-2.1: What kind of transformations does AM bring to the product creation process when considered as a technology for the production of functional end-use components?	AM influences the whole product creation process and beyond by altering its agility and reconstructing the iteration patterns among the design, engineering, and manufacturing activities. It triggers the organizational change both at the engineering and managerial levels and requires a modified skillset for efficient technology deployment.
RSQ-2.2: What kind of cost constituents an accurate analytical framework shall address when studying an AM-enabled production?	The framework shall account for the costs of labor, capital, consumables, and materials across the build preparation, printing, post-processing, and quality control stages of the AM-based production workflow.
RSQ-2.3: Which factors shall the framework study to cover an entire design space for an AM-enabled manufacturing system?	The framework shall cover the factors influencing the parts' costs allocation along the entire workflow; they include various aspects of the manufacturing process and system design and production planning.
RSQ-2.4: What kind of methods and tools shall comprise the framework to efficiently and accurately study an entire shop floor design space?	The framework shall combine the methods and tools necessary to fully define the case study data and the manufacturing system and accurately simulate all operations within it in time.
RSQ-3.1: What kind of linkages between the engineering and manufacturing domains shall have an integrated framework?	The framework shall have the inter-domain linkages connecting the product, process, and organization data involved in the model-based simulation of product development and manufacturing operations.
RSQ-3.2: What are the advantages and disadvantages of an integrated engineering and manufacturing planning approach?	The approach allows a comprehensive study of the time- and cost-based implications of the technical challenges that occur during the product creation process at the expense of a higher development effort and computational cost.

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Appendix

A1. A range of the Additive Manufacturing processes

The following information has been retrieved from (*AM Field Guide - Formnext - Mesago*, 2019).

formnext

ADDITIVE MANUFACTURING FOR POLYMER

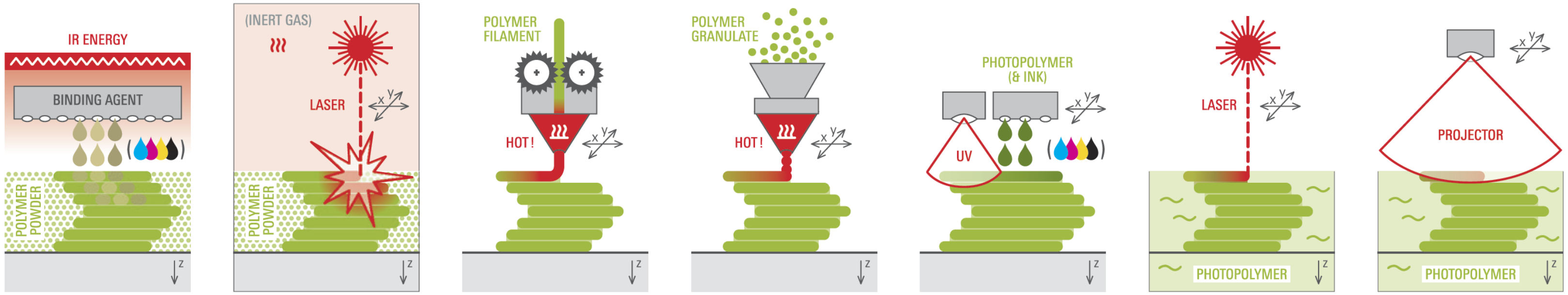
formnext.com

[4.2] Powder Bed Fusion
- Fused with agent + energy → **MJF** Multi Jet Fusion
- Fused with laser → **SLS** Selective Laser Sintering

[4.4] Material Extrusion
- Material extrusion Filament → **FDM** Fused Deposition Modeling
- Material extrusion Granulate → **APF** Arburg Plastic Freeforming

[4.6] Material Jetting
- Cured with UV light → **MJ** Material Jetting

[4.7] Photopolymerization
- Cured with laser → **SLA** Stereo Lithography
- Cured with projector → **DLP** Direct Light Processing



MJF

Kleinste Flüssigkeitströpfchen werden lokal auf eine Polymerpulverschicht aufgebracht. Sie erhöhen oder unterdrücken die Wärmeabsorption des Materials. Eine integral wirkende Infrarotquelle schmilzt das pulverförmige Ausgangsmaterial lokal auf.

Tiny liquid droplets are applied locally to a layer of polymer powder. They increase or suppress the heat absorption of the powder. An integrally acting infrared source melts the material respectively.

SLS

Mittels eines beweglichen Laserstrahls wird Polymerpulver schichtweise selektiv lokal gesintert und verfestigt damit einen Querschnitt des Bauteils.

By means of a movable laser beam, a polymer powder is selectively sintered locally layer by layer and thus solidifies a cross-section of the component.

FDM

Drahtförmiger Kunststoff, sogenanntes Filament, wird in einer Düseneinheit plastifiziert und schichtweise selektiv lokal dosiert.

Wire-shaped plastic, so-called filament, is plasticized in a nozzle unit and selectively dosed locally layer by layer.

APF

Kunststoffgranulat wird in einer Düseneinheit plastifiziert und schichtweise selektiv lokal dosiert.

Plastic granulate is plasticized in a nozzle unit and selectively dosed locally layer by layer.

MJ

Durch viele Düsen werden kleinste Photopolymertröpfchen lokal und schichtweise aufgebracht. Direkt im Anschluss wird das dickflüssige Photopolymer durch UV-Licht ausgehärtet.

Small droplets of photopolymer are applied locally and layer by layer through many nozzles. The viscous photopolymer is then cured instantly by UV-light.

SLA

Mittels eines beweglichen Laserstrahls wird ein dickflüssiges Photopolymer schichtweise selektiv lokal auspolymerisiert und verfestigt sich dort.

By means of a movable laser beam, a viscous photopolymer is selectively cured locally in layers and solidifies there.

DLP

Mittels eines Projektors wird ein Photopolymer schichtweise belichtet. Material, das belichtet wird, polymerisiert lokal aus und verfestigt sich.

A photopolymer is exposed layer by layer using a projector. The exposed material is polymerized locally and solidifies.

Für alle Verfahren gilt: Durch den schichtweisen selektiven Ablauf entstehen dreidimensionale Strukturen.

It applies to all processes: three-dimensional structures are created by the selective layer-by-layer process.

Stand: Oktober 2019 / *Status: October 2019*

formnext

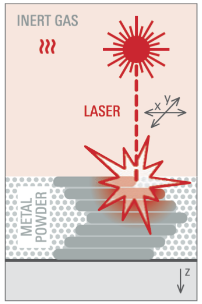
ADDITIVE MANUFACTURING FOR METAL

formnext.com

[4.2] Powder Bed Fusion

Fused with laser

SLM
Selective Laser Melting

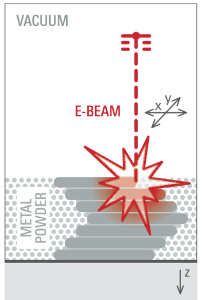


Mittels eines beweglichen Laserstrahls wird Metallpulver schichtweise selektiv lokal aufgeschmolzen und verfestigt damit einen Querschnitt des Bauteils.

By means of a movable laser beam, metal powder is selectively melted locally layer by layer, thus solidifying a cross-section of the component.

Fused with electron beam

EBM
Electron Beam Melting



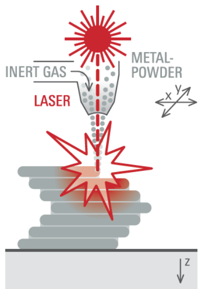
Mittels eines beweglichen Elektronenstrahls wird Metallpulver schichtweise selektiv lokal aufgeschmolzen und es verfestigt sich damit ein Querschnitt des Bauteils.

By means of a movable electron beam, metal powder is selectively melted locally layer by layer, thus solidifying a cross-section of the component.

[4.3] Direct Energy Deposition

Fused with laser

LENS
Laser Engineering Net Shape

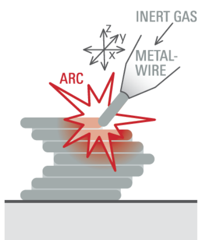


Material wird aufgebracht und simultan durch einen Laserstrahl aufgeschmolzen. Das folgende Erstarren der Schmelze generiert neue Schichten, die über- und nebeneinander angeordnet werden.

Material is applied and melted simultaneously by a laser beam. The following solidification of the melt generates new layers which are arranged above and next to each other.

Fused with electric arc

WAAM
Wire and Arc Additive Manufacturing



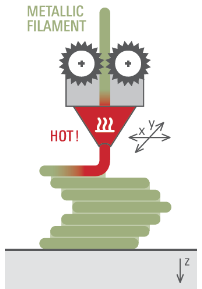
Metalldraht wird im Lichtbogenschweissverfahren geschmolzen und schichtweise lokal aufgetragen, um schnell große endkonturnahe Metallstrukturen zu erzeugen.

Metal wire is melted by arc welding and applied locally in layers to quickly produce large near-net-shape metal structures.

[4.4] Material Extrusion

Green part is printed to be sintered afterwards

FDM
Fused Deposition Modeling



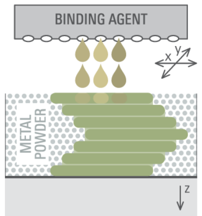
Drahtförmiger metallhaltiger Kunststoff, sogenanntes Filament, wird in einer Düseneinheit plastifiziert und schichtweise selektiv lokal dosiert.

Wire-shaped metal-containing plastic, so-called filament, is plasticized in a nozzle unit and selectively dosed locally layer by layer.

[4.5] Binder Jetting

Joined with bonding agent to be sintered afterwards

BJ
Binder Jetting



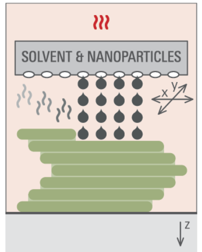
Winzige Bindemitteltropfen werden durch viele Düsen selektiv lokal und schichtweise auf Metallpulver aufgebracht. Sie kleben das Pulvermaterial zusammen.

Tiny binder droplets are selctively applied locally through many nozzels and in layers onto metall powder. They stick the powder material together.

[4.6] Material Jetting

Cured with heat to be sintered afterwards

NPJ
Nano Particle Jetting



Eine Metallpartikel-Lösemittelflüssigkeit wird in einer Düseneinheit selektiv lokal dosiert. Das Lösemittel verdampft und die Nanopartikel verbinden sich.

A metal particle solvent fluid is selectively dosed locally by a nozzle unit. The solvent evaporates and the nanoparticles bond together.

Für alle Verfahren gilt: Durch den schichtweisen selektiven Ablauf entstehen dreidimensionale Strukturen.

The following applies to all processes: three-dimensional structures are created by the selective layer-by-layer process.

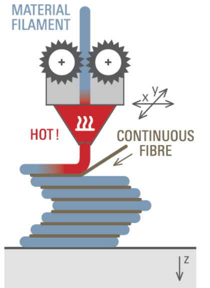
Stand: Oktober 2019 / *Status: October 2019*

ADDITIVE MANUFACTURING FOR OTHER MATERIALS

[4.4] Material Extrusion

Material extrusion COMPOSITE

CFF
Continuous Filament Fabrication

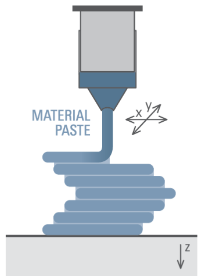


Drahtförmiger Kunststoff (Filament) wird in einer Düseneinheit plastifiziert und schichtweise selektiv lokal um kontinuierlich abgelegte Verstärkungsfasern herum dosiert.

Wire-shaped plastic (filament) is plasticized in a nozzle unit and selectively dosed layer by layer locally around continuously deposited reinforcing fibers.

Paste Extrusion ANY PASTY MATERIAL

PEM
Paste Extrusion Modeling



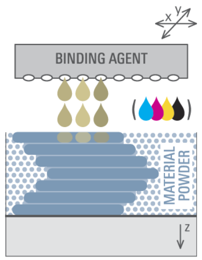
Material wird schichtweise selektiv lokal durch eine Kolben-Düsen- oder Pumpeneinheit dosiert.

Material is selectively dosed layer by layer locally by a piston-nozzle or pump unit.

[4.5] Binder Jetting

Joined with bonding agent SAND OR GYPSUM

BJ
Binder Jetting



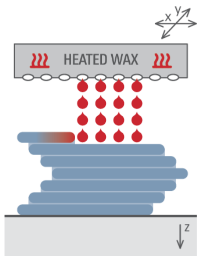
Winzige Bindemitteltropfen werden durch viele Düsen selektiv lokal und schichtweise auf das Pulverbett aufgebracht. Sie kleben das Pulvermaterial zusammen.

Tiny binder droplets are selctively applied locally through many nozzels and in layers onto the powder bed. They stick the powder material together.

[4.6] Material Jetting

Microdosed WAX

DOD
Drop on Demand



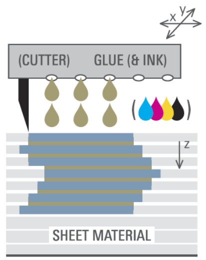
Durch viele Düsen werden erhitzte Wachströpfchen lokal selektiv und schichtweise aufgebracht. Durch Abkühlung verfestigt sich das Wachs.

Through many nozzles, heated wax droplets are applied locally selectively and layer by layer. The wax solidifies through cooling.

[4.8] Sheet Lamination

Laminated COMPOSITE OR PAPER

SDL / LOM
Selective Deposition Lamination / Laminated Object Manufacturing



Durch Düsen wird selektiv lokal Klebstoff auf die jeweilige Materialschicht aufgebracht. Die einzelnen Bauebenen werden direkt oder nachträglich gestapelt und laminiert, das Bauteil entlang der Kontur ausgeschnitten und / oder nachträglich freigelegt.

Nozzles are used to selectively apply locally adhesive to the respective material layer. The individual construction levels are stacked and laminated directly or subsequently, the component is cut out along the contour and/or subsequently uncovered.

Für alle Verfahren gilt: Durch den schichtweisen selektiven Ablauf entstehen dreidimensionale Strukturen.

The following applies to all processes: three-dimensional structures are created by the selective layer-by-layer process.

Stand: Oktober 2019 / *Status: October 2019*

A2. A list of metal allows printable by various additive manufacturing methods

The following information has been retrieved from (*What Metals Can You Print? | Digital Alloys*, 2020).

KEY: Commercially Available | In Development / Proven in Lab

		Metal Additive Manufacturing Process					
Primary Metal	Metal Alloy / Grade	Powder Bed Fusion	Binder Jetting	Powder DED	Wire DED	Joule Printing	Cold Spray
		feedstock: powder	feedstock: powder	feedstock: powder	feedstock: wire	feedstock: wire	feedstock: powder
Steel	A2 Tool Steel			In Development / Proven in Lab			
	H11 Tool Steel		In Development / Proven in Lab			In Development / Proven in Lab	
	H13 Tool Steel	Commercially Available	Commercially Available	Commercially Available		Commercially Available	
	M2 Tool Steel		Commercially Available				
	S7 Tool Steel			Commercially Available			
	P20 Tool Steel					In Development / Proven in Lab	
	S390 High Speed Steel	In Development / Proven in Lab					
	Maraging Steel	Commercially Available		Commercially Available	Commercially Available		
	Case Hardening Steel	Commercially Available					
	Stainless 13-8			Commercially Available			
	Stainless 15-5 PH	Commercially Available	In Development / Proven in Lab	In Development / Proven in Lab	In Development / Proven in Lab		
	Stainless 17-4 PH	Commercially Available	Commercially Available	Commercially Available	In Development / Proven in Lab		
	Stainless 300 series	Commercially Available	Commercially Available	Commercially Available	Commercially Available	In Development / Proven in Lab	
	Stainless 400 series	Commercially Available	In Development / Proven in Lab	In Development / Proven in Lab	In Development / Proven in Lab		
	4000 series	Commercially Available	In Development / Proven in Lab				In Development / Proven in Lab
	ERXXX				In Development / Proven in Lab	In Development / Proven in Lab	
Nickel	Pure Nickel			In Development / Proven in Lab		In Development / Proven in Lab	
	Inconel 625	Commercially Available	Commercially Available	Commercially Available	Commercially Available	In Development / Proven in Lab	Commercially Available
	Inconel 718	Commercially Available	Commercially Available	Commercially Available	In Development / Proven in Lab	In Development / Proven in Lab	In Development / Proven in Lab
	Inconel 738	Commercially Available					
	Inconel 939	Commercially Available		In Development / Proven in Lab			
	Alloy X	In Development / Proven in Lab					
	Haynes 188/282/230	In Development / Proven in Lab					
	Mar-M-247		Commercially Available	In Development / Proven in Lab			
	Waspaloy	Commercially Available		Commercially Available			
	Hastelloy (X, C276)	Commercially Available		In Development / Proven in Lab			In Development / Proven in Lab
	ABD 900AM	Commercially Available		In Development / Proven in Lab			
	Ni-Cr-Co-Ti (Rene XX)	In Development / Proven in Lab					
	Ni-Cu (Monel K-500)					In Development / Proven in Lab	In Development / Proven in Lab
	Ni-WC		In Development / Proven in Lab	In Development / Proven in Lab			In Development / Proven in Lab
	Ni-Ti	In Development / Proven in Lab				In Development / Proven in Lab	
Titanium	CP Ti (Grade 2)	Commercially Available		Commercially Available	Commercially Available	In Development / Proven in Lab	Commercially Available
	Ti-6Al-4V (Grade 5)	Commercially Available	Commercially Available	Commercially Available	Commercially Available	Commercially Available	In Development / Proven in Lab
	Ti-6Al-4V (Grade 23)	Commercially Available		Commercially Available	Commercially Available	Commercially Available	In Development / Proven in Lab
	Ti 4822			In Development / Proven in Lab			
	Ti 5553	In Development / Proven in Lab		In Development / Proven in Lab			
	Ti 6242			Commercially Available			
	Ti-C			In Development / Proven in Lab			
	Ti-Al	Commercially Available					
Cobalt	Pure Cobalt	In Development / Proven in Lab					
	MP1	Commercially Available					
	SP2	Commercially Available					
	Co-Cr	Commercially Available	Commercially Available				
	Co-Cr-Mo	Commercially Available		In Development / Proven in Lab			
	Co-Cr-W	In Development / Proven in Lab					
	Co-WC		In Development / Proven in Lab	In Development / Proven in Lab			
	Stellite 6/12/21/31			Commercially Available			
	T400/800			In Development / Proven in Lab			
	RPD	Commercially Available	In Development / Proven in Lab				
Copper	Pure	Commercially Available	Commercially Available	In Development / Proven in Lab	In Development / Proven in Lab	In Development / Proven in Lab	Commercially Available
	Cu-Al-O (Glidcop)	In Development / Proven in Lab	In Development / Proven in Lab				
	Cu-Sn	Commercially Available					
	Cu-Ni (C18XXX)	Commercially Available				In Development / Proven in Lab	
	Cu-Cr-Zr	Commercially Available					
	Cu-W	In Development / Proven in Lab	Commercially Available				
	Cu-Cr-Nb (GRCop-XX)	In Development / Proven in Lab		In Development / Proven in Lab			
	Bronze (Sn and Al)	Commercially Available	Commercially Available		In Development / Proven in Lab	In Development / Proven in Lab	In Development / Proven in Lab
Aluminum	Al-Si	Commercially Available					
	Al-Si-Mg (F357)	Commercially Available		In Development / Proven in Lab	In Development / Proven in Lab		
	Al-Si-Cu	Commercially Available					
	Al-Mg-Sc (scalmalloy)	Commercially Available		In Development / Proven in Lab			
	Al-Cu-Ti-B2 (A205/A20X)	Commercially Available		In Development / Proven in Lab			
	Al 1000	In Development / Proven in Lab				In Development / Proven in Lab	
	Al 2000 series				In Development / Proven in Lab		
	Al 4000 series			Commercially Available	In Development / Proven in Lab	In Development / Proven in Lab	
	Al 5087				In Development / Proven in Lab		
	Al 6061	In Development / Proven in Lab		In Development / Proven in Lab	In Development / Proven in Lab		Commercially Available
	Al 7075	In Development / Proven in Lab		In Development / Proven in Lab	In Development / Proven in Lab		In Development / Proven in Lab
Refractory	Tungsten Heavy Alloy		Commercially Available		In Development / Proven in Lab		
	Tungsten Carbide	In Development / Proven in Lab		Commercially Available			In Development / Proven in Lab
	Tungsten Carbide-Cobalt	In Development / Proven in Lab	Commercially Available				
	Tantalum	In Development / Proven in Lab			In Development / Proven in Lab	In Development / Proven in Lab	
	Molybdenum	In Development / Proven in Lab			In Development / Proven in Lab	In Development / Proven in Lab	
	Niobium	In Development / Proven in Lab				In Development / Proven in Lab	
Magnesium	WE43	In Development / Proven in Lab					
	Mg-Al (AZ XXX)	In Development / Proven in Lab			In Development / Proven in Lab		In Development / Proven in Lab
Lead	200	In Development / Proven in Lab					
	325	In Development / Proven in Lab					
Tin	325	In Development / Proven in Lab				In Development / Proven in Lab	
	800	In Development / Proven in Lab				In Development / Proven in Lab	
Iron	Invar (36)	Commercially Available		In Development / Proven in Lab	In Development / Proven in Lab		In Development / Proven in Lab
	Pure Iron	In Development / Proven in Lab					
	Fe-Ni (HR-1)	In Development / Proven in Lab		In Development / Proven in Lab			
Precious	Gold	Commercially Available				In Development / Proven in Lab	
	Platinum	Commercially Available				In Development / Proven in Lab	
	Palladium	Commercially Available				In Development / Proven in Lab	
	Silver	Commercially Available				In Development / Proven in Lab	
Misc.	Zinc / Brass					In Development / Proven in Lab	In Development / Proven in Lab
	Zirconium					In Development / Proven in Lab	
	Halfnium					In Development / Proven in Lab	
	High Entropy Alloys	In Development / Proven in Lab		In Development / Proven in Lab			

A3. Interview protocol

The list below summarizes the interview protocol used in the case study researching the transformations triggered by additive manufacturing (AM) in the firm's organization and product development (PD) practice. It delineates major stages of the interview (in **bold**), the possible topic areas (if multiple), and the typical questions (in *italic*).

1. **Introducing the purpose of the research.**
    a. Research motivation: understanding the influence of additive manufacturing on the allocation of product development efforts in engineering organizations.
    b. Research context: brief introduction of the MIT Work of the Future Task Force and the aspiration to study the impact of new technologies on the jobs and business organization.
    c. Research objective A: investigate the AM's impact on the structure and parallelism of the PD activities.
    d. Research objective B: identify the skillset transformation supporting the technology adoption.
2. **Describing confidentiality and signing the Consent Form.**
3. **Describing the format of the interview.**
4. **Familiarizing with the subject.**
    i. *At a high-level, what is you role at the Company?*
    ii. *Could you describe your involvement in the development of an additively manufactured component of study?*
    iii. *Were you also involved in the development of the conventionally manufactured component of study?*
    iv. *Can you describe your experience with the Company's product development practice and your professional background?*
5. **Open conversation.**
    a. Mapping the PD process.
        i. *Can you describe the product development process at the Company? What are its major stages?*
        ii. *What are the typical employees' functions in each stage?*
        iii. *How long does each stage usually take?*
        iv. *Which stages can be performed simultaneously and which sequentially?*

v. *What kind of product development activities can cause the rework of the previous activities? Can you give the specific examples and/or describe the formal steps?*

b. Understanding the effects of AM.

i. *Have you noticed any specific differences in the product development process when working on the additively manufactured component of study?*

ii. *Would you say that AM-based process requires more or less stages of product development?*

iii. *Has AM affected the parallelism of the product development activities?*

iv. *Do you find AM increasing or decreasing the rework probabilities after any specific operations?*

c. Understanding the skillset transformation.

i. *What characteristics, skills, or personality traits of yours or your colleagues you found important for developing AM-produced components?*

ii. *Do you find these characteristics, skills, or personality traits also useful in the conventional context?*

6. Clean-up.

7. Wrap-up.

A4. A detailed design structure matrix of the integrated change management reference process

Name	#	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22	23	24	25	26	27	28	29	30	31	32	33	34	35	36	37	38	39	40	41	42	43	44	45	46	47	48	49	50	51	52	53	54	55	
1. Screen for potential integrated change (IC)	1	1	x																																																						1
Identify the IC (product and manufacturing engineers)	2	x	2	x	x			x		x	x																																														2
Create the IC profile for change cause	3		x	3	x																																																				3
Identify and inform stakeholders about the potential IC	4			x	4	x	x	x																																																	4
Review and update risk and impact rating	5			x	x	5	x		x																																				x												5
Collect information and define the change requirements	6			x	x	x	6	x			x																																														6
Identify deviations between requirements and current	7			x	x		x	7																																					x												7
Assess target deviation	8							x	8																																																8
Preliminary review of change need	9								x	9																																											x				9
Decide on the release of a change request	10								x	x	10																																														10
2. Make a detailed problem and target description	11						x				x	11		xx								x			x				x	x																		x	x	x							11
Develop and describe solution concept proposals	12											x	12	x		x																																									12
Make change and change propagation analysis	13												x	13																																											13
Make stakeholder review	14											x	x	x	14																																										14
Estimate and approve the invest plan	15												x	x		15	x																																								15
Prepare solution concept proposals for IC	16											x	x	x	x	x	16	x																																							16
3. Evaluate solution concept proposals and make pre-selection	17																x	17	x	x	x	xx								x			x												x												17
Align solution concept proposal(s) with the customer	18																	x	18		x															xx																					18
Conduct manufacturability analysis	19																	x		19	x																																				19
Make detailed cost analysis	20																	x	x	x	20																																				20
Select and approve the solution concept	21																	x	x	x	x	21											x																								21
4. Develop an IC in detail (detailed EC + conceptual MC)	22																					x	22	x		x	x	x	x	x															x												22
Conduct manufacturability analysis	23																						x	23	x					x																											23
Implement the EC	24																						x	x	24	x																															24
Check implemented EC	25																						x		x	25		x																													25
Make quality and performance test	26																						x		x	x	26			x																											26
Review and update the information systems	27																						x		x			27		x																											27
Review and evaluate the EC	28																								x	x	x	x	28																								x				29
Approve detailed change plan - Collaborative decision	29																							x					x	29				x																							30
Release EC	30																													x	30																										31
Review MC profile and prepare the concepts	31																													x	x	31	x																								32
Approve MC solution concept and release the change order	32																														x	x	32	x																							33
5. Select and integrate suppliers	33																													x			x	33	x	x	x													x							34
Plan the MC in detail	34																						x										x	x	34	x	x	xx		xx	x																35
Align detailed change plan with the customer	35																																	x	x	35	x																				36
Make the sourcing plan proposal	36																																	x	x	x	36		xx		x																37
Approve the detailed change plan	37																																		x			37																			38
Approve the sourcing plan	38																																				x	x	38																		39
Compile the final detailed change plan	39																																						x	39																	40
Make the implementation plan proposal	40																													x					x		x			x	40	xx	xx				xx										41
Approve an implementation plan	41																																						x		x	41															42
Procure the technical equipment	42																																									x	42														43
Assign the roles and responsibilities	43																																									x	x	43	x	x							x				44
Review the change plan	44																																									x		x	44	x							x				45
Review the MC profile	45																																									x		x	x	45											46
Approve the MC to be implemented	46																																													x	46										47
6. Implement MC	47																																															47	xx	xx							48
Check the implemented IC	48																																															x	48								49
Make quality and performance test	49																																																x	49							50
Review and update the information systems	50																																															x	x	x	50						51
Make an overall "go for production" check	51																																																x	x	x	51					52
7. Review and evaluate the IC	52										x						x					x								x			x							x							x						52				53
Describe and highlight the lessons learned	53																																																				x	53			54
Clean up	54																																																				x		54		55
Close the IC	55																																																				x	x	x	55	56

A5. The list of qualitative and quantitative cost modeling assumptions of the LPBF workflow

#	Workflow step	Qualitative assumptions	Labor quantitative assumptions	Value	Unit	Capital quantitative assumptions	Value	Unit	Consumables quantitative assumptions	Value	Unit	Material quantitative assumptions	Value	Unit
1	Simulation initiation	We define the machines and their quantity in the beginning of the simulation; these machine are dedicated only to the specified parts				Machine purchase cost (see the machines table)								
	- Capital investment: definition of hour cost for each machine	Workers are: engineers, operators, technicians, quality control (QC) engineers				Infrastructure cost (small..large machine)	50..25	%						
	- Definition of workers quantities	Uptime rate is taken is taken under assumption that the factual rate would not be higher				Maintenance cost rate (small..large machine)	5..10	%						
	- Setting the start week day (Monday)	Capital cost parameters are defined for each machine in the input matrix				Lifetime	7	years						
	- Shift mode (24/7 or 5/2)	For each part the first qualitative control parameter- Internal Quality (IQ) in % of the best case for porosity, cracks, voids etc. occurrence - is assumed to be measured online within the AM process				Discount rate	5	%						
	- Read parts data (including GD&T)	The second control parameter - Geometrical Dimensions and Tolerances (GD) on critical dimensions to measure with CMS - will be measured at the QC station				Uptime rate	65	%						
		The parts with IQ defects move to scrap after band saw				Shift duration	9	hr						
		The more defects in a part the higher the countermeasure cost for it												
		Buffers are unlimited in size												
		After QC the parts can go to rework (at PP), scrap, or drain												
2	Queue the parts in accordance with estimated production time and time given	Definition of the parts sequence list to follow throughout the simulation												
		Support removal time is linearly proportional to post-processing complexity												
3	Selection of the printer	1st order preference - minimal time gap preference 2nd order preference - maximum machine hour cost												
		Review the plate area use after the assignment process: if the value is small - select the smallest available printer												
		For each part we define the set of applicable printers by checking the limitations with L, W, H; the parts are assumed to not be positioned along the diagonals												
4	Engineer prepares the build following one of three strategies (BP)	Takes the parts sequence list and follows the BP strategy	Engineer hour rate	60	$	Plate effective area (small..large machine/diameter)	80..90	%				Raft height	5	mm
		Mixed max fill strategy is filling the whole plate with different part types	Full time equivalent (FTE)	100	%	Compactness coefficient; defines how close the parts can be to each other by increasing the area of each part	110	%				Raft base area (as % of parts base area)	70	%

		Single strategy is putting only one part on the plate	Time to prepare a new part type	30	min	Software annual license per workplace	6000	$				Raft mass is distributed homogeneously		
		Max fill strategy is filling the whole plate with one part type	Time to prepare the part second time	2	min									
		Total cost of preparing the build are distributed evenly among all parts in the build	Time to prepare the build identical second time (only if it has already been issued)	5	min									
			Max build prep time	300	min									
			Number of engineers is set equal to the number of BP stations											
5	STL file goes to the printer's entrance buffer	Each printer has its own queue												
6	Operator installs the build plate	Installation time follows the normal distribution	Mena time to install the plate	20	min	Machine rent for setup	20	min	Plate cost (small..large)	25..250	$			
			FTE	100	%				Number of build plate refurbishments, i.e., milling ~0.1mm each time	20				
			Operator hour rate	40	$									
7	Operator refills the powder hoppers if there is not enough powder for the next build	Necessary powder volume equals to the product of plate area and the sum of a highest part in the build and the raft height	Time to refill	25	min	Volume of the refill hopper as a factor of the build chamber volume	1.5							
		Time follows the normal distribution	FTE engineer	100	%	Time to be set up	25	min						
8	Machine is flushed to inert, warm up	Inertion and warm up happen simultaneously	FTE engineer	15	%	Time to inert and warm up the machine; it is a machine parameter (small..large)	30...120	min	Pre-print inerting as a factor build chamber volume	10	L			
									Gas cost	0.018	$/L			
									Electricity cost	10	cents/kWt			
									Electricity consumption rate as a factor of the power consumption during printing	0.5	kWt-hr			
9	Printing process	Currently, material usage is not correlated with operator's experience	FTE engineer	15	%	Printing time equals to the sum of ratio between the build mass and build rate and the the total recoating time		min	Operating cost per hour during printing includes gas and electricity consumption; costs scale with the build time, and therefore support-included mass of the part (small..large machine)	5..20	$/hr	Steel powder cost	50	$/kg
		If the printing finishes during the night in a 5/2 shift mode, then machine is waiting until the morning for build exchange				Layer recoating time	2	sec				Titanium powder cost	200	$/kg
		Machines are dedicated to a particular material; it is assumed, that having hours- or days-long machines setup for new material shall be excluded from the analysis at this stage				Process accuracy	96	%	In-process inerting rate as a factor of the build chamber volume	3	L/min	Aluminum powder cost	57	$/kg
		Parts length, width, and height are given as they stay in the build				Inspection error of a hypothesized in situ inspection system	1	%	Build plate cost for M400; the other machines' plates costs are defined proportionally to the area	250	$			
		"Internal Quality" (IQ) objective (95%) indicates a fraction of "good" material structure, i.e., ~5% are for, e.g., pores and micro cracks. It is assumed, that the inspection goes online and "remembers" IQs for each part within the build				Cost of the inspection infrastructure, i.e., the hardware and software	0	$	Refurbishment capacity, i.e., the number of times it is possible to refurbish the plate	10	$			

		The standard deviation if IQ is constant and equals to 1/3 of the difference between the nominal value and the lower specified limit; i.e., to ensure 99.7% of parts are expected to have a good quality							Cost of refurbishment	25	$			
		Real values of IQ follow the normal distribution; its mean equals a product of the target value and the Process accuracy parameter that is a fraction between 0 and 1 (where 1 designates a 100% accuracy)												
		At this step, the system also defines the "as Inspected" values (which deviates from the real value given an error in the measurement system)												
		The parts with IQ defects continue the process until removed with the band saw; the system immediately orders a new part when the defect is found, i.e., right after printing												
		True defects are those parts which asPrinted , i.e., a real value and asInspected, i.e., measured value are less than the lower specified limit												
		False defects are those which asInspected value is lower and asPrinted is larger than the lower specified limit												
		True non-defective parts have both asPrinted and asInspected larger than the lower specified limit												
		False non-defective parts have asPrinted lower and asInspected larger than the lower specified limit; customer compensation would be necessary in this case												
		asInspected mean equals to asPrinted value from the distribution												
10	Machine cools down		FTE engineer	15	%				Electricity costs	10	cents/ kWt			
11	Build plate removal	Removing means unscrewing and brushing away the powder	FTE engineer	100	%									
		Time follows normal distribution	Mean time to remove the plate	15	min									
		If there is not enough time to complete build exchange and cleaning before the night/pause, then machine waits until the end of the night/pause; then the operator comes and carries the part to the buffer system												
12	Filters exchange, lens cleaning, argon gas tank exchange	Time follows the normal distribution	FTE engineer	100	%									
13	Machine cleaning and regular maintenance after each 3 builds		Maintenance time	30	min	Time for regular maintenance	30	min						
			FTE	100	%									
14	In parallel to steps 10-13, the powder is recycled	Assumed to be automated	FTE	0	%							Recyclable fraction	90.5	%
15	Machine preventive maintenance	Happens once per week	FTE	100	%	Time for preventive maintenance	180	min						
16	Build moves to the after-print buffer	Operator moves the builds	FTE engineer	100	%									

17	Operator runs the heat treatment of the build	Heat treatment time is the same for all builds	FTE operator - build exchange	100	%	Duration of heat treatment	120	min	Cost of operating the furnace	1.9	$/hr			
		Normal distribution for the build exchange time	FTE operator - supervision	15	%									
		A one hour preventive maintenance happens once per 30 days	Mean time to install the build	5	min									
			Mean time to remove the build	5	min									
18	Operator transports the build to the cool down spot	Cool down duration is 1 hour (taken less than HT)	FTE technician to move the build	100	%									
19	Technician installs the build on the band saw		FTE technician - build exchange	100	%									
			Technician rate	20	$/hr									
20	Sawing the build	Sawing the raft (and therefore its area)	FTE technician - machining	100	%	Sawing time for the steel plate of 100 mm diam.	16.75	min	Blade cost	400	$			
			Number of technicians is equal to the number of the band saw and build prep. stations						Blade lifetime	20	hours			
21	Put the parts in the buffer	Plates go to recycling												
	Put the IQ defects into scrap													
22	Install the part for finishing	Normal distribution	Mean installation time	3	min									
			FTE technician	100	%									
23	Finishing operation	Time is proportional to the volume of supports on the part	Time to remove the supports	formula	min									
		Separate buffer for parts on rework (priority to parts on rework)	FTE technician	100	%									
		asProduced "real" value is assigned here	Rework time is always 1.5 times less											
			Supports removal rate	30	ccm/hr									
24	Final quality inspection	Normal distribution of asInspected value	QA engineer	60	$/hr	Inspection error (CMS)	0.1	%						
		asInspected mean equals to asProduced value	Inspection time (const)	10	min	Inspection time (const)	10	min						
		If asInsp < LSL then it is the defect (for the Shaft); If asInsp > USL the send to rework (for the Shaft). The opposite rules for the Hole	FTE	100	%									
		Quality-loss costs to be assigned here to the parts that were sent to the final drain	Number of QA engineers equals to the number of QA stations											
		Cost of countermeasure is const: doesn't depend on the quantity of defects and their types, i.e., IQ or GD&T												
		Cost of countermeasure is defined in the parts Input file: what the manufacturer will pay if the defect would reach the customer												
		Quality loss cost function is k*(y-m)^2												
		y equals the asInspected value												
25	Put the finished part on the shelf	Normal distribution	Mean time to send the part	3	min									
			FTE technician	100	%									

List of Abbreviations

ABC	Activity-Based Costing
ACR	Advanced Concepts Review
AM	Additive Manufacturing
ATC	Analytical Target Cascading
BA	Bleed Air
CAD	Computer-Aided Design
CAE	Computer-Aided Engineering
CCM	Cubic Centimeter
CCM	Concurrent Change Management
CDR	Critical Design Review
CER	Cost Estimating Relationship
CMM	Coordinate Measuring Machine
CNC	Computer Numerical Control
CPS	Cyber-Physical System
DES	Discrete Event Simulation
DfAM	Design for Additive Manufacturing
DfM	Design for Manufacturability
DMM	Domain Mapping Matrix
DSM	Design Structure Matrix
DT	Digital Twin
EBM	Electron Beam Melting
EC	Engineering Change
ECM	Engineering Change Management
EDM	Electrical Discharge Machining
EJ	Expert Judgement
FFF	Form, Fit, Function
GD&T	Geometric Dimensioning and Tolerancing

GDP	Gross Domestic Product
GRNN	General Regression Neural Network
HIP	Hot-Isostatic Pressing
ICM	Integrated Change Management
IoT	Internet of Things
KPI	Key Performance Indicator
LDA	Latent Dirichlet Algorithm
LPBF	Laser Powder Bed Fusion
MC	Manufacturing Change
MCM	Manufacturing Change Management
MDM	Multidomain Matrix
PBF	Powder Bed Fusion
PCB	Printed Circuit Board
PD	Product Development
PDM	Product Data Management
PDP	Product Development Process
PDR	Preliminary Design Review
PLM	Product Lifecycle Management
PPR	Product, Process, and Resources
PRR	Production Readiness Review
QC	Quality Control
R&D	Research and Development
RR	Requirements Review
SASIG	Strategic Automotive product data Standards Industry Group
SBCE	Set-Based Concurrent Engineering
SBD	Set-Based Design
SLM	Selective Laser Melting
SME	Small and Medium-sized Enterprises
STL	Standard Tessellation Language
TRL	Technology Readiness Level
USD	United States Dollar

WIP	Work In Progress
WBS	Work Breakdown Structure
XCT	X-ray Computed Tomography

List of Figures

List of Tables