UNIVERSITY OF LATVIA

Summary of
Doctoral Thesis

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A SOFTWARE ARCHITECTURE FOR INTEGRATING ADDITIVE MANUFACTURING INTO ENTERPRISE PRODUCTION SYSTEMS

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SUMMARY OF DOCTORAL THESIS

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ABSTRACT

This dissertation presents a software architecture for integrating Additive Manufacturing (AM) into cyber-physical production systems. Traditional manufacturing environments, supported by ERP and PPC systems, lack the structural flexibility to accommodate the non-task-specific and dynamic nature of AM processes. This work develops a Production Planning and Control (PPC) system tailored to AM, enabling seamless coordination with existing enterprise systems.

Following the principles of Design Science Research, the architecture was iteratively designed, implemented, and validated through simulation. Key contributions include a modular software architecture for AM-specific process control, a dynamic resource allocation engine, and a real-time production order generator. The system enables interoperability with ERP systems, supports decentralized manufacturing networks, and integrates real-time data feedback to adapt to varying production constraints.

The work addresses core challenges in information systems development (ISD) for manufacturing, including system design for highly flexible environments, data flow integration across heterogeneous sources, and the embedding of AM-specific logic into existing industrial IT infrastructure. Supplementary modules demonstrate the feasibility of leveraging machine learning for predictive scheduling and blockchain for decentralized order management, further extending the architecture's potential in Industry 4.0 ecosystems.

Keywords: Additive Manufacturing (AM), Production Management, Operations Management, Production Planning and Control (PPC), System Architecture, Enterprise Resource Planning (ERP), Design Science Research Methodology (DSRM)

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INTRODUCTION

Additive Manufacturing (AM) is a core enabling technology within the context of Industry 4.0 and Enterprise Production Systems (EPS). AM is one of the technologies which enables the digital-to-physical transformation, thus turning the traditional EPSs into Cyber-Physical Production Systems (CPPSs), which are digitally integrated production systems that connect physical manufacturing processes with computational control systems. This transformation is part of AM's revolutionary impact on manufacturing within the context of the fourth industrial revolution, where digitalization, automation, and interconnected systems enable new approaches to product development and production across aerospace, automotive, medical, and consumer goods industries [1]. Recent systematic reviews highlight the transformative potential of cyber-physical production systems in enabling smart manufacturing capabilities [2]. Traditional subtractive manufacturing methods involve removing material from workpieces using specialized tools and sequential operations, while AM builds objects layer by layer directly from digital models without requiring dedicated tooling. Unlike these traditional approaches, AM offers design freedom, resource efficiency, and the possibility of decentralized production. This integration challenge is part of the broader digital transformation toward Industry 4.0, where cyber-physical systems offer significant potential by unifying technological approaches including big data analysis and artificial intelligence to enhance real-time monitoring and control of manufacturing processes [3]. In practice, this integration is hampered by the fact that current Enterprise Resource Planning (ERP) and Production Planning and Control (PPC) systems, which coordinate business processes and manufacturing operations, are primarily designed for linear, predefined process flows. AM, by contrast, is characterized by task-unspecific production capabilities, meaning the ability to produce different parts without retooling or reconfiguration, as well as non-linear workflows, and high degrees of reconfigurability. This results in a fundamental architectural mismatch between existing software systems and the operational logic of AM, leading to inefficiencies, planning gaps, and manual workarounds. This dissertation addresses this gap by proposing a modular, extensible software architecture for AM-specific PPC integration within EPS environments. The architecture is designed to enable dynamic resource management, real-time feedback mechanisms, and seamless interoperability with enterprise IT systems such as ERP and Manufacturing Execution System (MES).

Research problem

The industrial deployment of AM introduces a fundamental shift in how manufacturing processes are planned, controlled, and executed. Traditional production systems—based on subtractive or formative processes—are structured around task-specific machines arranged in fixed sequences, where each work step requires dedicated tooling, setup, and coordination. These environments are well-supported by established PPC systems and enterprise software solutions such as ERP. In contrast, AM technologies operate with production units capable of performing the same generic process, allowing for significant flexibility in job scheduling and resource allocation. This uniformity changes the entire planning logic: instead of orchestrating diverse production steps across specialized equipment, AM requires the management of multiple production units with identical capabilities, aiming to maximize throughput through intelligent grouping and dynamic assignment of jobs. This fundamental difference in production logic is recognized by industry practitioners and indicates that the architectural differences between traditional and additive manufacturing extend beyond technical specifications to encompass fundamentally different operational paradigms.

Existing PPC architectures are often unable to represent the operational behavior of AM. Key limitations include the lack of process-based routing mechanisms, inflexible assignment of resources, and insufficient support for late-stage decision-making, which refers to the ability to modify production parameters close to or during execution, or decentralized job execution. Contemporary research emphasizes the need for real-time control architectures specifically designed for additive manufacturing environments [4]. AM's process characteristics, such as long but unattended execution times, tool-less production, and the decoupling of job setup from part geometry, further challenge conventional production models and control flows. The integration of AM into enterprise manufacturing environments is therefore not just a matter of connecting machines to software, it requires a fundamentally different architectural approach. Without redesigning the underlying coordination logic, AM will remain decoupled from the digital production backbone, leading to fragmented workflows, manual workarounds, and underutilized production potential.

Research purpose, thesis, and tasks

This dissertation addresses the need for a software architecture that allows AM to become a fully integrated component of CPPSs.

The purpose of this dissertation is to design a solution that enables continuous coordination across multiple AM units, supports dynamic job orchestration, and remains interoperable with existing ERP-based environments without disrupting the established production control ecosystem.

Thus, the following *research thesis* can be formulated to be put forward for the defense: *the industry-scale introduction of Additive Manufacturing (AM) in the manufacturing environment established by Traditional Manufacturing Technologies (TMT) can be enabled with the development of appropriate process management and process control solutions.*

The deployment of AM in industrial production environments requires software systems that can support its unique process characteristics without compromising existing IT infrastructures or production control logic. AM differs fundamentally from Traditional Manufacturing Technologies (TMT) in terms of its setup-free operation, job flexibility, and decoupling from task-specific workflows. These differences present challenges for conventional PPC systems, which are not designed to handle such dynamic, process-centric production resources.

To fulfill on the purpose of this dissertation, the overarching *task* can be formulated: *to develop a software architecture for AM-specific Production Planning and Control (PPC) and its integration with the traditional Enterprise Production Systems (EPS) to enable controllable and manageable Cyber-Physical Production Systems (CPPSs).*

The overarching task can be further divided into more specific research tasks (RTs):

- **RT1**: *Determine and describe the functional scope of existing PPC systems in manufacturing, to identify process control tasks which support industrial-scale operations (Chapter 1).*
- **RT2**: *Identify and describe essential characteristics of AM, which make this technology incompatible with traditional PPC logic and ERP-integrated production systems (Chapter 1).*
- **RT3**: *Propose a solution which allows overcoming the identified architectural and operational incompatibilities between AM and the TMT manufacturing environments (Chapter 3).*
- **RT4**: *Propose a solution which allows taking advantage of the novel features of AM, particularly its flexibility in resource assignment and responsiveness to change, without disrupting the process control function of the legacy manufacturing systems (Chapters 3 and 4).*

Combined, research tasks RT1 through RT4 establish the scope for the research work in this thesis. They guide the design of the software architecture, the selection of implementation methods, and the definition of evaluation scenarios.

Research methodology

This research adopts the Design Science Research Methodology (DSRM) as the primary methodological framework. DSRM is particularly suitable for the development of software artifacts, as it supports iterative refinement, context-aware problem solving, and rigorous evaluation. The design process follows the six core activities of DSRM:

1. Problem Identification and Motivation: Empirical analysis of the limitations of existing PPC systems in handling AM-specific production workflows.
2. Definition of Objectives for a Solution: Derivation of architectural and functional requirements based on the unique characteristics of AM and the constraints of industrial IT integration.
3. Design and Development: Construction of a modular software architecture featuring a production order generator and coordination logic for resource-aware job assignment.
4. Demonstration: Implementation of the architecture in a simulation environment that reflects realistic manufacturing scenarios and production constraints.
5. Evaluation: Measurement of system performance using key metrics such as throughput, resource utilization, and responsiveness under varying workloads.
6. Communication: Documentation and dissemination of findings to both the academic and industrial communities through this dissertation and related publications.

By following this methodology, the research ensures both scientific rigor and practical relevance, enabling the systematic design, implementation, and assessment of a software architecture that addresses real-world challenges in integrating AM into CPPSs.

To fulfill the development task several modern analysis and data processing methods were used. Simulation-based evaluation is used to test system performance under varying production scenarios. Machine learning techniques are applied for predictive production time modeling based on sensor data and process parameters. Optimization algorithms, including nesting and packing algorithms, are implemented for efficient build space utilization. Blockchain technology is utilized for secure coordination in decentralized production networks.

Scientific contribution

This dissertation contributes to the field of Information Systems by providing a software architecture that bridges the gap between AM processes and enterprise-level PPC systems. While AM is well-studied from a materials and mechanical perspective, its integration into industrial IT environments remains underexplored from a software engineering viewpoint.

The key scientific contributions of this work are:

- A domain-specific reference architecture for AM-oriented PPC, capturing process-based order generation, dynamic resource scheduling, and real-time data integration in CPPS.

- A functional software prototype that implements the architecture and demonstrates its viability through simulated production scenarios involving machine availability, job pooling, and material-specific job grouping.
- A methodological framework for integrating AM into existing ERP landscapes through modular interfaces, enabling synchronization of order and status data with minimal system intrusion.
- A simulation-based evaluation strategy, tailored to the requirements of CPPSs environments, including key performance indicators such as responsiveness, utilization, and scheduling flexibility.
- Demonstration of architectural extensibility, illustrated through optional modules leveraging machine learning for process time prediction and blockchain for distributed order coordination.

By addressing both architectural design and practical implementation, this work provides a foundation for future research and industrial applications in the area of smart manufacturing and CPPSs-driven production control.

Approbation of the research results

Research findings reported in this thesis have been published in the following scholarly articles indexed in Elsevier Scopus or/and Web of Science databases:

1. Schuhmacher, Jan, Baumung, Wjatscheslav and Hummel, Vera. "An Intelligent Bin System for Decentrally Controlled Intralogistic Systems in Context of Industrie 4.0". Procedia Manufacturing 9 (2017): 13542. https://doi.org/10.1016/j.promfg.2017.04.005. (Author's contribution 80%: conceptualization, software, writing, data curation, methodology, visualization)
2. Baumung, Wjatscheslav, and Fomin, Vladislav V. "Optimization Model to Extend Existing Production Planning and Control Systems for the Use of Additive Manufacturing Technologies in the Industrial Production". Procedia Manufacturing 24 (2018): 22228. https://doi.org/10.1016/j.promfg.2018.06.035. (Author's contribution 80%: conceptualization, software, writing, data curation, methodology, visualization).
3. Baumung, Wjatscheslav, and Fomin, Vladislav V. "Increasing the utilization of Additive Manufacturing resources through the use of blockchain technology for a production network". c 13 (2018): 134-141. https://hdl.handle.net/20.500.12259/36849. (Author's contribution 80%: conceptualization, software, writing, data curation, methodology, visualization).
4. Baumung, Wjatscheslav, and Fomin, Vladislav V. "Framework for Enabling Order Management Process in a Decentralized Production Network Based on the Blockchain Technology". Procedia CIRP 79 (2019): 45660. https://doi.org/10.1016/j.procir.2019.02.121. (Author's contribution 80%: conceptualization, software, writing, data curation, methodology, visualization).

5. Baumung, Wjatscheslav, Glöckle, Herbert, and Fomin, Vladislav V. "Production Planning and Control (PPC) system architecture for the use in networked Additive Manufacturing (AM) facilities". In the proceedings of the 11th scientific conference "New Challenges of Economic and Business Development: Incentives for Sustainable Economic Growth" (2019): 64-71. https://doi.org/10.22364/ncebd.2019. (Author's contribution 80%: conceptualization, software, writing, data curation, methodology, visualization).
6. Roth, Armin, and Baumung, Wjatscheslav. "Digitalization As Enabler for a Holistic Corporate Performance Management". Quarterly Review of Business Disciplines (QRBD) Volume 7 May (2020): 53-63. https://faculty.utrgv.edu/louis.falk/qrbd/QRBDnov20.pdf. (Author's contribution 50%: conceptualization, software, writing, data curation, methodology, visualization).
7. Baumung, Wjatscheslav. "Design of an Architecture of a Production Planning and Control System (PPC) for Additive Manufacturing (AM)". Business Information Systems (BIS) June (2020): 391-402. https://doi.org/10.1007/978-3-030-53337-3_29.

Research findings included in this thesis have also been reported in the following scholarly publications that are not indexed in Elsevier Scopus or Web of Science databases:

8. Baumung, Wjatscheslav, Glöckle, Herbert, and Fomin, Vladislav V. "Blockchain als Enabler eines dezentralen Produktionsnetzwerkes". Industrie 4.0 Management (2019): 3942. https://doi.org/10.30844/I40M_19-1_S39-42. (Author's contribution 80%: conceptualization, software, writing, data curation, methodology, visualizatio).
9. Baumung, Wjatscheslav, and Fomin, Vladislav V. "Predicting production times through machine learning for scheduling Additive Manufacturing orders in a PPC system". IEEE International Conference of Intelligent Applied Systems on Engineering (ICIASE) (2019): 47-50. https://doi.org/10.1109/ICIASE45644.2019.9074152. (Author's contribution 80%: conceptualization, software, writing, data curation, methodology, visualization).

The diversity of perspectives on the research problem led to conferences of the respective viewpoints being used to discuss knowledge about the respective topic and to share the knowledge with the corresponding research community. The research results reported in this thesis were presented at the following conferences:

1. Roth, Armin, and Baumung, Wjatscheslav (2018): "Digitalization as enabler for a holistic performance management", 30th annual Conference of the International Academy of Business Disciplines (IABD), from 6th to 8th April 2018, San Francisco, (USA)
2. Baumung, Wjatscheslav (2018): "Optimization Model to Extend Existing Production Planning and Control Systems for the Use of Additive

Manufacturing Technologies in the Industrial Production", 4th International Conference on System-Integrated Intelligence: Intelligent, Flexible and Connected Systems in Products and Production, from 19th to 20th of June 2018, Hannover (Germany)
3. Baumung, Wjatscheslav (2018): "Increasing the utilization of Additive Manufacturing resources through the use of blockchain technology for a production network", Joint Proceedings of Baltic DB&IS 2018 Conference Forum and Doctoral Consortium co-located with the 13th International Baltic Conference on Databases and Information Systems (Baltic DB&IS 2018), from 1st to 4th July 2018, Trakai (Lithuania)
4. Baumung, Wjatscheslav (2018): "Framework for Enabling Order Management Process in a Decentralized Production Network Based on the Blockchain-Technology", 12th CIRP Conference on Intelligent Computation in Manufacturing Engineering, from 18th to 20th July 2018, Gulf of Naples (Italy)
5. Baumung, Wjatscheslav (2019): "Predicting production times through machine learning for scheduling Additive Manufacturing orders in a PPC system", IEEE International Conference of Intelligent Applied Systems on Engineering (ICIASE), from 27th to 30th April 2019, Fuzhou, Fujian (China)
6. Baumung, Wjatscheslav (2019): "Production Planning and Control (PPC) system architecture for the use in networked Additive Manufacturing (AM) facilities", 11th international scientific conference "New Challenges in Economic and Business Development 2019: Incentives for Sustainable Economic Growth", from 16th to 18th May 2019, Riga (Latvia)
7. Baumung, Wjatscheslav (2020): "Design of an architecture of a production planning and control system (PPC) for Additive Manufacturing (AM)", 23rd International Conference on Business Information Systems 2020 (BIS), from 8th to 10th June 2020, Colorado Springs (USA)

Structure of the thesis

This thesis is structured according to the principles of Design Science Research and proceeds in a logical sequence from the identification of the research problem to the development, implementation, and evaluation of a system-oriented solution. Chapter 1 introduces the theoretical foundation of production systems and AM. It establishes the conceptual constructs of traditional PPC, highlights the specific characteristics of AM, and identifies architectural incompatibilities that motivate the need for system redesign. Chapter 2 outlines the research paradigm and methodology. It presents the philosophical foundation of Design Science Research, describes the adopted research process based on the Design Science Research Methodology (DSRM), and explains the derivation of research objectives and evaluation criteria. Chapter 3 details the design of a system architecture for AM integration into existing production environments. It includes a conceptual PPC model, defines process-specific planning and control methods, and outlines a strategy for integrating AM technologies into traditional manufacturing contexts. Chapter 4 covers the technical implementation of the proposed system. It describes the structure and behavior of the software prototype and explains how the developed components were instantiated and tested in a simulation environment. Chapter 5 presents the research results, discusses the contribution to system-oriented research and artifact-based knowledge development, and evaluates the feasibility and adaptability of the proposed system architecture. The thesis concludes with a summary of key findings, practical recommendations, and an outlook for future research directions.

1. THEORETICAL FOUNDATION OF ADDITIVE MANUFACTURING INTEGRATION IN PRODUCTION IT SYSTEMS

The industrial integration of AM into existing production environments presents both conceptual and architectural challenges. AM technologies enable tool-less, geometry-independent production with high process flexibility, characteristics that stand in contrast to the structured, sequential, and often tool-dependent logic of traditional manufacturing systems. As a result, the operational behavior of AM does not align well with the assumptions embedded in current PPC and Enterprise Resource Planning (ERP) systems.

Chapter 1 provides the theoretical and technical foundation for addressing AM integration challenge from a computer science perspective. It begins by introducing the key constructs and operational models of traditional production systems (Section 1.1), followed by an overview of enterprise-level information systems (Section 1.2). Section 1.2.1 examines the structure and objectives of ERP systems and their evolution from manufacturing-centric resource planning toward integrated business control platforms. Section 1.3 focuses on PPC systems as the functional core of production execution, highlighting the planning horizons, control logic, and information structures they encapsulate. Section 1.4 establishes the conceptual completeness of the construct space, synthesizing the essential aspects of both traditional manufacturing and AM. It abstracts AM into generalized process phases and identifies the requirements that arise when these are mapped onto enterprise IT structures. Section 1.5 builds on this analysis by identifying specific architectural incompatibilities between AM and traditional PPC systems, including differences in process variability, resource allocation, workforce specialization, and scheduling logic. To overcome the identified incompatibilities, two seemingly contradictory characteristics of AM must be reconciled: the very high product variety inherent to AM and the high production volume typical of traditional mass production systems (Figure 1).

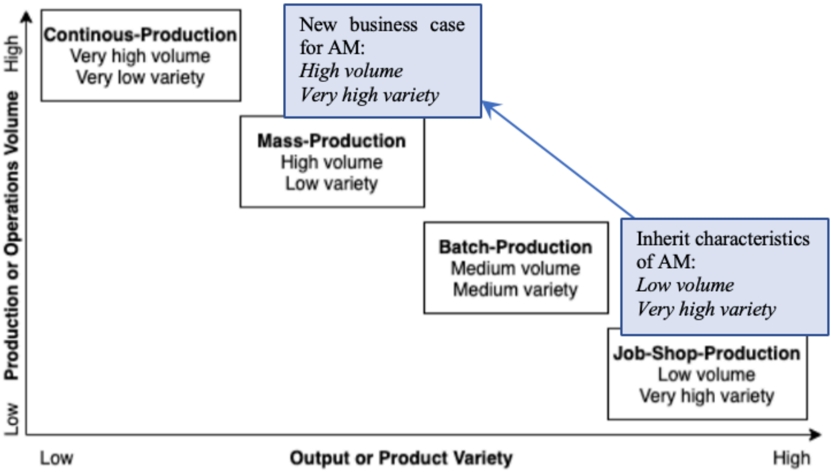

Figure 1. **New business case for AM: implementation of AM on industrial scale**

Source: Author's representation adapted from Anil Kumar and Suresh [5, p. 3]

This chapter concludes by positioning the AM integration challenge as a system architecture problem that requires the redefinition of planning logic, data models, and control mechanisms. The identified incompatibilities provide the technical design requirements for the development of modular, integrable components, which are addressed through models and methods in the subsequent chapters.

2. RESEARCH METHODOLOGY FOR DESIGNING THE SYSTEM ARCHITECTURE

This chapter presents the research paradigm and methodological framework used for the design and validation of a software architecture that enables the integration of AM into CPPS. Given the complexity and novelty of the problem domain, the Design Science Research (DSR) paradigm was selected. Design Science originated from engineering and computer science and focuses on the development and evaluation of artifacts that provide solutions to practical and application-oriented problems [6]. Design Science aims to create new knowledge through the construction of purposeful artifacts such as models, methods, and systems, and to validate them through rigorous evaluation.

The chapter outlines the research paradigm and methodological foundation. It justifies the suitability of DSR for investigating system-level integration challenges and articulates how this paradigm supports both theoretical abstraction and practical implementation. The design methodology is introduced by detailing the sequential and iterative phases followed throughout the research process. Each activity is described in relation to the overall research objectives. By formalizing the research process through DSR, this chapter ensures both methodological rigor and traceability of design decisions. The resulting software architecture is not only validated against defined problem scenarios but is also positioned as a generalizable solution framework for embedding AM-specific logic within enterprise-scale production control systems.

To date, a number of methodological frameworks for Design Science Research – commonly referred to as Design Science Research Methodology (DSRM) – have been developed. DSRM entails a number of distinctive steps (or stages) with slight differences in how the steps are called or in what sequence they appear [7]. In this thesis, DSRM framework suggested by Peffers et al. is adopted [8]. This framework divides the entire research process into 6 activities [8] (see Figure 2):

1. “*Problem identification and Motivation*” - Establishes the specific research problem and indicates the increased value of the required solution.
2. “*Define the objectives for a solution*” - Solution objectives are extracted from the problem and analyzed for feasibility based on specific knowledge.
3. “*Design and development*” - Providing artifacts in the form of art structures, models, methods, or instantiations.
4. “*Demonstration*“ - Explains the demonstration of artifacts in order to show specific aspects of problem solving.

5. *"Evaluation"* - Observes and evaluates artifact to validate the contribution in the problem-solving space.
6. *"Communication"* - Communicate the research findings with the significance of the problem and the artifact developed with its contribution to problem resolution.

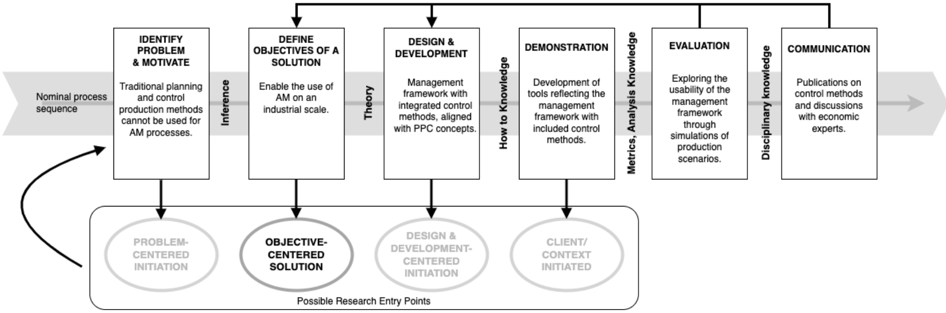

Figure 2. **Conducted research process according to the DSRM model of Peffers et al. [8]**

Although the research process provides for the sequential processing of activities, Peffers et al. points out that the entry point for research can vary depending on the type of problem and the solution goal. The starting point for this research is the „Objective-Centered Solution". This implies that the research is motivated by an objective to develop a solution for a specific known problem.

The transformation of the tasks defined in the DSRM model is carried out through an iterative design process focused on the development of the artifact: a system architecture composed of a computational model for AM enabled production planning and control, along with the domain-specific logic required to support process coordination and execution.

Through the iterations in the research process, various models for production planning and control are analyzed, contributing to comprehensive new knowledge on the state and functionality of the PPC system for enabling AM in the traditional manufacturing environment: the knowledge on how the various business scenarios with changing order situations are leading to changing production requirements, and how changes in the available resources are leading to the changing order of production. By identifying "causal links and exploring the consequences of changing … relationships" [9, p.1144], this new knowledge represents a *novel theory* "in the abstract form of models, methods, [and] principles" [10, p.361].

3. DESIGN A PPC SYSTEM ARCHITECTURE FOR ENABLING AM

Chapter 3 presents the design of a system architecture that enables the integration of AM into existing PPC environments. Building on the identified requirements and architectural incompatibilities outlined in Chapter 1, and informed by the methodological approach described in Chapter 2, the architecture is developed as a structured set of planning and control models tailored to AM-specific characteristics (Figure 3).

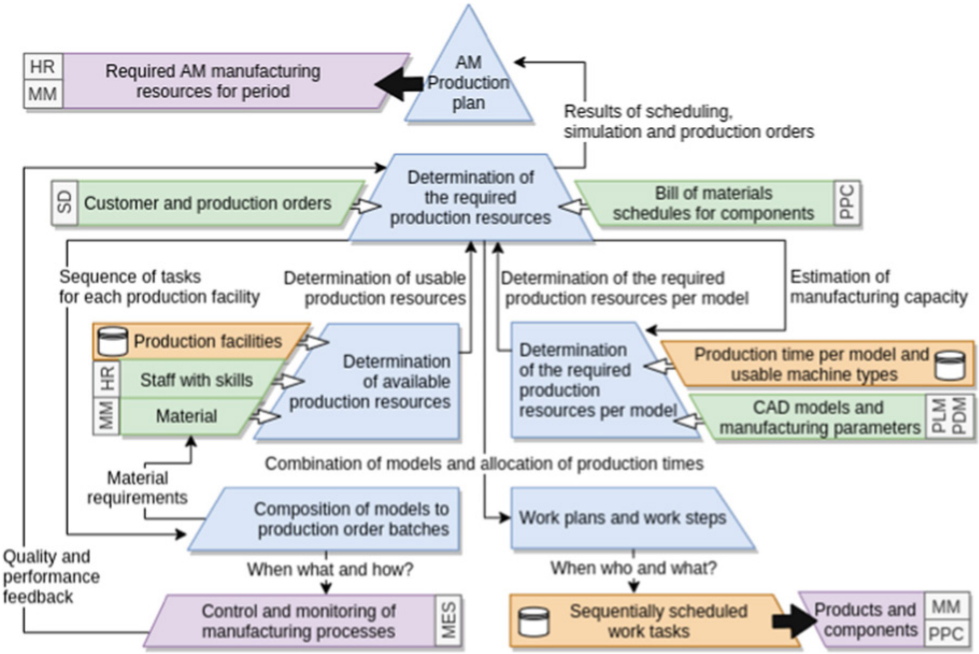

Figure 3. Architecture for an AM-PPC with planning components and interconnected ERP modules

Source: Author's illustration published in article [1]

The proposed architecture model is constituted by functional areas such as planning, scheduling, monitoring, and resource coordination, with each function aligned to AM-specific requirements. Subsequent sections of Chapter 3 describe the derivation of design requirements, the structure of the proposed architecture, and the development of methods for integrating AM into system-based production environments. The results provide the foundation for implementing a flexible, scalable, and context-aware control system that supports the industrial use of AM within established IT and organizational infrastructures.

3.1. Architecture of AM PPC system

Due to the many interrelated processes along the product-related data, the development of the architecture of the PPC system for AM production facilities requires a multi-layer model. For this purpose, the product-related data from the areas of human resources, materials management, sales department and product lifecycle management must be considered in interaction with Production Management. The interconnected nature of tasks within these modules means that changes in one area can impact both current and subsequent processes. The proposed architecture model incorporates numerous process-affecting variables. These include alterations in customer and production orders from the Sales Department (SD) module, employee availability from the Human Resources (HR) module, and resources such as machines and CAD models from the Product Lifecycle Management (PLM) module.

The proposed AM-PPC architecture follows established principles of layer-based system design for comprehensive performance management. This multi-layer approach enables systematic data flow from acquisition through analysis to visualization, supporting both operational control and strategic decision-making [11]. The architecture integrates information into operational process flows and enables efficient use of corporate resources, where data can be collected, analyzed and checked for interconnection both internally and externally. This foundation is particularly crucial for AM integration, as it supports the complex data dependencies and real-time coordination requirements inherent in CPPS.

The initial step in planning is to assess the production assets at hand, including workforce, materials, and machinery. Subsequently, these assets are evaluated against the needed resources, such as CAD designs and client requests. To discern the requisite resources, a unique machine code for each model within each type of facility is generated. This code facilitates the extraction of parameters through simulation of the manufacturing process, which aids in ascertaining resource requirements and labor time for each production line. The resulting data, linked to the CAD model as production parameters, reflects the variability in parameters among models of the same type. Should a model be replaced, for instance due to an update, new manufacturing parameters must be recorded. The demands for batch production are derived from the bill of materials (PPC) and sales orders (SD). This is done by maximizing the use of the production space within a facility, while considering the upper limit of time available. Compatible models are arranged using a nesting or packing algorithm. The methods section details the precise steps for the time-efficient arrangement of items. One restriction, for example, is the free combination of different models due to the specific grouping requirement. Grouping involves assembling parts simultaneously, necessary for putting individual components together. Grouped parts can be allocated across multiple printers for subsequent stages to ensure a sequential workflow. For these processes, routings with the necessary steps are mapped out. The sequential nature of the work is preserved, with the finish time of one line and the job duration setting the completion schedule for the subsequent line. The manufacturing lines are then directed by the MES, which also logs and responds to anomalies like faults in a line, potentially calling for technician intervention and noting changes in machine status. The end products or components are identified as output parameters, with the distinction hinging on whether they stem from a customer or a production order—production orders necessitate further steps and subsequent planning in the traditional PPC system. Ultimately, the combination of products and components in a production order depends on the available production resources.

3.2. Adaptation requirements of the existing PPC

The competing goals of PPC are production with high adherence to schedules and flexibility, with uniformly high capacity utilization, but with small stocks in the warehouse and workshop [12]. These goals are achieved by scheduling, capacity and quantity planning and control of production [13]. In order to incorporate these goals into the operational areas of responsibility, the Aachen PPC [14] model divides the functional groups into two basic areas, the core tasks for order processing and the cross-sectional tasks for cross-departmental tasks (Table 1). The core tasks consist of long-term and medium-term production and demand planning as well as short-term and medium-term in-house production and external procurement planning [15, p.243]. Cross-divisional tasks, on the other hand, deal with overlapping tasks such as order coordination, warehousing and PPC controlling.

Table 1. **Core and cross-sectional tasks of a PPC**

Core tasks	Cross-sectional tasks
Production planning • Sales plan • Inventory planning • Primary requirements planning • Resource rough planning **Production demand planning** • Gross secondary demand determination • Net secondary requirements determination • Procurement type assignment • Lead time scheduling • Determination of capacity requirements • Capacity coordination **In-house production planning and control** • Lot size calculation • Fine scheduling • Detailed resource planning • Sequence planning • Availability check • Order release • Order monitoring • Resource monitoring **External procurement planning and control** • Order invoice • Tender request and evaluation • Supplier selection • Order release • Order monitoring	**Order coordination** • Offer processing • Order clarification • Order rough scheduling • Resource rough planning • Order management **Warehousing** • Warehouse movement management • Inventory control • Storage location and storage bin • management • Batch management • Stock control • Inventory **PPC-Controlling** • Information processing • Information evaluation • Configuration

Source: Author's illustration based on [16]

The subsequent analysis of AM integration requirements for each core task area was structured using two evaluation criteria. The "Data Input Required" indicated whether the task requires external data inputs from other system modules or real-time production data. The "Planning Logic Component" identified tasks that require new or modified planning algorithms specifically adapted for AM process characteristics, such as build space optimization or time-aware scheduling. In order to achieve the goal of integrating AM into the known production processes of industrial manufacturing, the core tasks of PPC systems were examined and adapted to the specific AM process requirements.

3.3. Efficient use of building space in consideration of a given period of time

The key challenge of AM implementation in industrial manufacturing facilities is the integration of many process optimization and control techniques reviewed in Chapter 3 to create production orders. For an economically efficient use of installation space in AM, production orders must be planned in such a way that completion times and locations are considered together with machine and personnel availability. For this the areas of detailed scheduling and sequence planning of PPC are of decisive importance. Beyond scheduling optimization, the implementation of real-time process control during manufacturing can further enhance build space utilization by preventing build failures that would otherwise require reprinting, thereby maximizing the effective use of available production capacity [4]. **The integration of time-oriented optimization with space utilization represents a key architectural challenge in AM production systems.** This challenge requires systematic frameworks for formalizing AM production planning problems, as traditional nesting and scheduling concepts must be extended to address the unique subproblems inherent in additive manufacturing, such as proper part orientation and efficient placement of heterogeneous parts in the same build cycle [17].

For production orders to be completed and started within working time, it is necessary to dynamically assign the objects to be printed between the available printers. Production orders are not assigned to a production line with a certain number of fixed objects and then executed again and again, as would be the case with traditional manufacturing processes, but are staggered and generated dynamically according to the capacity utilization, demand and availability of the production resources.

Therefore, a model is presented here with which the nesting algorithms for the installation space utilization are extended by the time-based aspect, whereby a synchronization to the personnel availability can be achieved (Figure 4). This model provides the basis for scheduling and sequencing of AM. This model is based on the author's published work [18].

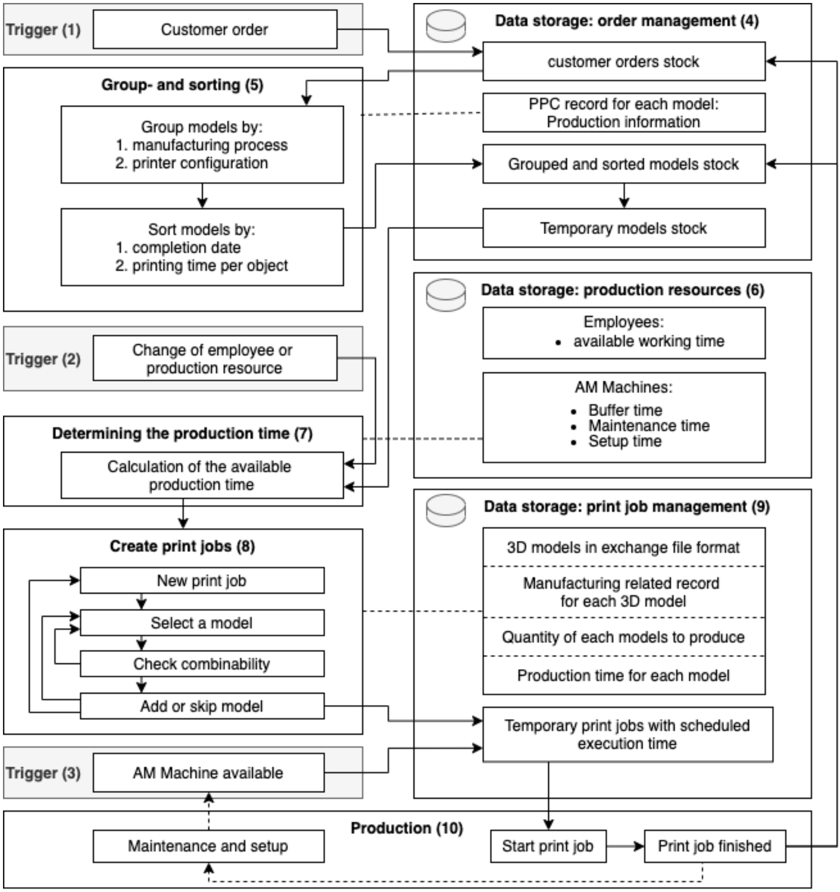

***Figure 4.* Optimization model for time-oriented planning of production orders for AM**

Source: Author's illustration published in [18]

The developed optimization model for time-oriented planning of production orders for AM shows the procedure for creating production orders from the input parameters customer orders (1), changes of production resources (2) and availability of production facilities (3). The three triggers cause the model to run through different process areas. The process flow with the different triggers and activities is described in detail in Chapter 3 of the dissertation. This dynamic approach is essential because the economic and environmental benefits of AM are highly dependent on production parameters such as volume, part geometry, and material efficiency, requiring intelligent planning systems that can optimize these factors while considering the hidden costs associated with energy-intensive feedstock production and slower production rates [19].

3.4. Development of methods for AM specific characteristics

To address specific challenges in integrating AM into enterprise level PPC systems, two complementary methods were developed that extend the proposed system architecture. These methods focus on predictive scheduling through machine learning (ML) and decentralized order coordination through blockchain (BC) technology.

3.5 Machine learning for predictive scheduling

Accurate forecasting of production times is a critical requirement for planning efficiency in AM environments, as print durations vary depending on geometry, material, and process parameters. To address this, a machine learning module was developed and integrated into the PPC architecture. Using simulation and sensor-based datasets, regression models were trained to predict build times based on slicing parameters, layer height, infill density, and material type. These models allow the PPC system to anticipate production duration more precisely and adjust job sequencing dynamically. This approach improves the systems planning precision and enables a more data-driven response to fluctuating workloads.

The data foundation for developing and validating the predictive models is illustrated in Figure 5, which shows the execution of a production order and the logging of all relevant processing times within the AM process chain. These recorded time series provided the empirical basis for training and testing the machine learning algorithms. Building on this dataset, a training structure was established that considered both direct process parameters, such as geometry and slicing configuration, and indirect factors like machine utilization or environmental conditions. The resulting models were validated through simulation cycles comparing predicted and actual build durations, allowing continuous refinement of forecasting accuracy.

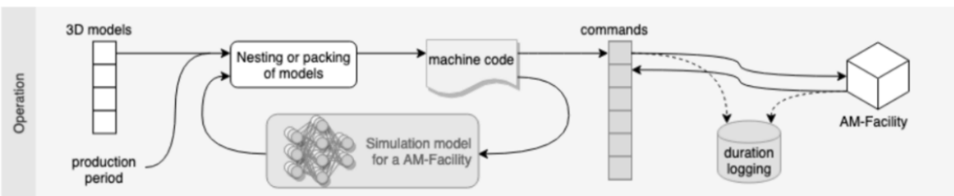

***Figure 5.* Execution of a production order with logging of the processing times**

Source: Author's illustration published in article [20]

By combining detailed process logging with data-driven model training and simulation-based validation, the developed machine learning module provides a foundation for predictive scheduling within the AM-PPC system. It enables the transition from static planning to adaptive, self-learning production control, thereby increasing the overall efficiency and reliability of additive manufacturing operations.

3.6. Blockchain for decentralized order coordination

As AM increasingly supports distributed and networked production scenarios, data integrity and trust among participating facilities become essential. To address these challenges, a blockchain-based coordination module was developed and integrated into the PPC architecture. This module enables the secure, transparent, and tamper-proof exchange of production orders and status data among decentralized manufacturing partners. Smart contracts are employed to automate order validation, confirmation, and tracking within the PPC, ensuring traceability while reducing administrative overhead and manual coordination efforts.

The implemented concept allows production partners to interact within a shared digital environment, where all transactions and order-related events are permanently recorded in a distributed ledger. This structure ensures that every participant has access to consistent and verifiable information about order status and execution progress. By eliminating centralized intermediaries, the system reduces communication latency and potential errors while increasing accountability and trust across the network.

The blockchain module was evaluated through a simulation of a decentralized production network representing multiple autonomous manufacturing sites. The results demonstrated that decentralized coordination can improve the reliability and efficiency of order management by providing transparent execution and automatic enforcement of contractual rules. These findings confirm the potential of blockchain technology as an enabling mechanism for secure and efficient collaboration in distributed production environments, supporting the broader goal of digitally integrated and autonomous manufacturing systems.

4. IMPLEMENTATION

Chapter 4 presents the implementation of the developed solution for generating production jobs from structured product data, demonstrating the software realization of key components of the proposed AM production planning and control system. **The implemented generator for print jobs constitutes a central control module within the system architecture, translating bill-of-material (BOM)-based part definitions into executable production orders**. These records, typically derived from product BOMs, may also include customer-specific or spare parts. To evaluate the functional scope and performance of the implemented generator, a test dataset comprising two products with a total of 57 unique and 75 overall parts was used. This dataset served as a reference for demonstrating core system functionalities and is introduced in more detail throughout the subsequent sections. The implementation highlights how digital process logic can be operationalized to support scalable and efficient AM production planning. This implementation approach follows established principles for AM production order generation that have been validated in networked production environments, where dynamic scheduling and resource coordination are essential for achieving optimal throughput [21].

In order to perform simulation runs with a close approximation to reality, two products with a large number of printed parts were selected as the data set. These two products were selected due to their high part variance in terms of size and manufacturing time. The first product represents a self-replicating rapid prototyping machine RepRap. The second product is the Mostly Printed CNC (MPCNC), an open-source CNC machine that, as the name suggests, follows the RepRap idea and consists mainly of printed parts and standard materials [22] see Figure 6).

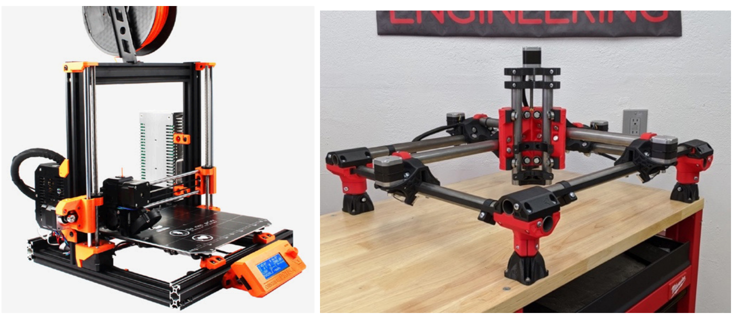

***Figure 6.* Product 1 the Prusa 3D printer with parts printed in orange (left) and Product 2 the MPCNC milling machine with parts printed in black and red (right).**
Source: PRUSA RESEARCH, 2022 and V1 Engineering 2020

The Prusa 3D printer consists of 32 different parts with a total number of 39 parts, the largest of which is 11.4cm × 18.5cm × 3.5cm. The MPCNC milling machine, on the other hand, consists of 25 different parts with a total number of 53 parts, where the largest part is 14.8cm × 7.5cm × 14.0cm.

4.1. Generator for the print jobs

The generator is divided into 4 stages. The starting point are the bills of materials with the corresponding 3D models in *stl* format. The first and second stage lead to the collection of information about each part, such as manufacturing time, dimensions and positioning. The third stage creates a sequence of parts to be considered for part generation. The fourth and final stage generates the print jobs.

4.1.1. Collecting information through slicing

For the collection of information about the required manufacturing time of each individual product part, it is sliced automatically based on the developed application flow. For slicing, the open source PrusaSlicer [23] is used, which is a fork of Slic3r [24] list. Automated slicing is performed by using the Command Line Interface (CLI). The CLI can be used to perform a large number of operations in a batch and as part of complex workflows. For slicing using the CLI, three configuration data are specified in addition to the 3D model in *stl* format and the target directory. The configuration data consists of the configurations for the 3D printer itself, the material and the print settings.

In addition to the already known name and path to the *stl* file, the production time in seconds and the material consumption in grams were added as a result of slicing. The number comes from the described bill of materials for the product and serves in the subsequent course for the generation of all print jobs for a product. The automated slicing execution by the program flow leads the product MPCNC to the following data set (see Table 2).

From the data shown in Table 2, an accurate picture of the manufacturing effort for the MCNC milling machine can now be derived. It can be seen that the Core part has the longest production time of over 21 hours, also requiring the highest consumption at over 197 grams. In total, the production time for all 53 parts of the milling machine amounts to 6 days, 1 hour and 38 minutes, with a material consumption of 1.28 kilograms. The same calculations were performed for the second product the Prusa 3D printer, as described in detail in Chapter 4.

Table 2. **Overview of the information added by slicing for the second evaluation data set for the MPCNC milling machine product** (fields with a gray background have been added)

Part	Qty	Print time (hh:mm:ss)	Material consumption (gr)
Core	1	21:53:38	197.49
Core Clamp	3	1:53:08	15.06
Core Clamp Y	1	1:42:15	14.09
Core Z Clamp 1	2	0:43:08	3.64
Core Z Clamp 2	2	0:43:11	3.64
Corner Bottom Mirrored	2	4:47:04	43.18
Corner Bottom	2	4:47:14	43.18
Corner Leg Lock	4	1:44:20	16.59
Corner Top Mirrored	2	4:07:51	37.4
Corner Top	2	4:06:23	37.39
Feet	4	2:59:28	28.16
Lower Belt Mirrored	2	0:45:18	6.0
Lower Belt	2	0:45:22	5.99
Lower Tool Plate	1	1:02:33	7.08
Nut Trap	2	0:54:46	7.28
Stop Block	4	0:41:18	5.02
Truck Mirrored	2	9:19:40	83.48
Truck	2	9:19:35	83.47
Truck Clamp	4	0:38:02	4.64
Upper Belt Mirrored	2	0:45:42	6.28
Upper Belt	2	0:45:50	6.28
Upper Tool Plate	1	0:40:01	4.6
Wire Darryl	2	0:11:17	1.34
Z Coupler	1	3:08:03	28.04
Z Motor	1	3:15:36	29.21

Source: Author's illustration

4.1.2. Information collection from 3D models

In addition to the information obtained from the slicing process, further manufacturing-relevant information can be obtained from the 3D models themselves. These are developed in the second stage of the program flow for the information extraction of the AM-PPC and described in this stage. The 3D models are provided in the *stl* file format, which describes the models by triangular facets and their vertices. For the processing of the vertices the Python numpy-stl package [25] was used, which provides methods for reading the vertices. From the analysis of the individual corner points, two essentially relevant pieces of information for the AM-PPC can be generated by determining the maximum values in the positive and negative areas of the coordinate system.

4.1.3. Generation of the sequence and a queue

While the first two stages were purely for obtaining information from the input data, from this and the following stage onwards this data is processed itself. In this stage, a queue is built up with a sequence in which the models are considered one after the other for the formation of the print jobs. For this purpose, the models are first sorted according to their manufacturing time starting with the longest manufacturing time. Thereby also duplicates are created on the basis of the parts list number, for example the number 4 for the part LCD-cable-clip leads to the fourfold occurrence of this part in the queue at the same place of the sequence.

As a result, a completely sorted queue is obtained in which the parts can be taken out after scheduling for a print job. The following table shows the queue for the MPCNC product for the first 10 parts, with the order in which the parts are considered one after the other for the creation of the print jobs (see Table 3).

Table 3. **Queue with order for the first and last 10 parts of evaluation product MPCNC**

Nr.	Part	Print time	Nr.	Part	Print time
1	Core	21:53:38	44	Stop Block	0:41:18
2	Truck Mirrored	9:19:40	45	Stop Block	0:41:18
3	Truck Mirrored	9:19:40	46	Stop Block	0:41:18
4	Truck	9:19:35	47	Upper Tool Plate	0:40:01
5	Truck	9:19:35	48	Truck Clamp	0:38:02
6	Corner Bottom	4:47:14	49	Truck Clamp	0:38:02
7	Corner Bottom	4:47:14	50	Truck Clamp	0:38:02
8	Corner Bottom Mirrored	4:47:04	51	Truck Clamp	0:38:02
9	Corner Bottom Mirrored	4:47:04	52	Wire Darryl	0:11:17
10	Corner Top Mirrored	4:07:51	53	Wire Darryl	0:11:17

Source: Author's illustration

4.1.4. Creating the print jobs

This stage is the most comprehensive and final stage of the print job generation. The basis for this is primarily the queue, as well as all the information generated in the previous steps, such as manufacturing time, the bounding box and absolute positioning in the coordinate system. In addition, there is data about the available manufacturing time per print job, the distance between the parts and the definition of the dimensions of the usable installation space of the printers.

After all data generated in the previous stages have been read in, parts are taken according to the sorting of the queue and checked according to the following points whether they can be added to a print job:

1. Check if the available manufacturing time is sufficient for the manufacturing time of a part;
2. Creation of a rectangle based on the bounding box of the part and check by nesting algorithm if there is enough space for this part in the build space.

If both points apply, the part is removed from the queue. The process is then repeated with the next part in the queue. If one of the previous two points does not apply, the part is not removed from the queue and the process is repeated with the next part. This process repeats until the last part in the queue. This approach addresses the AM-specific production planning challenges identified in recent frameworks, which emphasize the need for systematic solutions to technology-specific problems including part placement optimization and production order processing that differ fundamentally from traditional manufacturing planning approaches [60].

4.2. Evaluation of the implementation with simulation data

The implementation execution for the MPCNC evaluation product results in 7 print jobs, which are listed in Table 4 and can be seen in Figure 7.

A conspicuous problem is the print job with ID 4, where the production time exceeds the specified time. To solve this problem, there are two possibilities. On the one hand, after it has been determined that the available production time is exceeded, a part within the print job should be removed and exchanged for one with a shorter production time. For this purpose, the nesting process can be interrupted and the part can be exchanged for one with the next shorter production time. For the exchange, however, all the processes described would have to be repeated from nesting onwards. Alternatively, an attempt can be made to exchange a part from the print job for one with a shorter production time in a print job with much more remaining production time, for example a part from the print job with ID 7. This would have the advantage that only the parts in the print job with ID 4 and 7 would change and therefore only for these two the described procedure would have to be carried out from nesting. Here however the complexity is clearly higher to select the suitable parts and print orders, as simply a full new calculation. In the end, the choice of the more suitable solution can be determined by the available calculation capacities.

Table 4. **Generated print jobs for the evaluation product MPCNC milling machine**

Job ID:	Parts included	Print time calculated (hh:mm:ss)	Print time from gcode (hh:mm:ss)
1	Core, Core Clamp, Wire Darryl	23:58:03	23:59:52
2	Truck Mirrored, Truck Mirrored, Corner Bottom, Wire Darryl	23:37:51	23:32:48
3	Truck, Truck, Corner Bottom	23:26:24	23:30:25
4	Corner Bottom Mirrored, Corner Bottom Mirrored, Corner Top Mirrored, Corner Top Mirrored, Corner Top, Core Clamp	23:49:21	24:30:27
5	Corner Top, Z Motor, Z Coupler, Feet, Feet, Feet, Feet, Lower Tool Plate	23:30:27	23:05:28
6	Core Clamp, Corner Leg Lock, Corner Leg Lock, Corner Leg Lock, Corner Leg Lock, Core Clamp Y, Nut Trap, Nut Trap, Upper Belt, Upper Belt, Upper Belt Mirrored, Upper Belt Mirrored, Lower Belt, Lower Belt, Lower Belt Mirrored, Lower Belt Mirrored, Core Z Clamp 2, Core Z Clamp 2, Core Z Clamp 1, Core Z Clamp 1, Stop Block 23_5, Stop Block 23_5, Truck Clamp	23:19:55	21:56:44
7	Stop Block 23_5, Stop Block 23_5, Upper Tool Plate, Truck Clamp, Truck Clamp, Truck Clamp	3:56:43	3:37:50

Source: Author's illustration

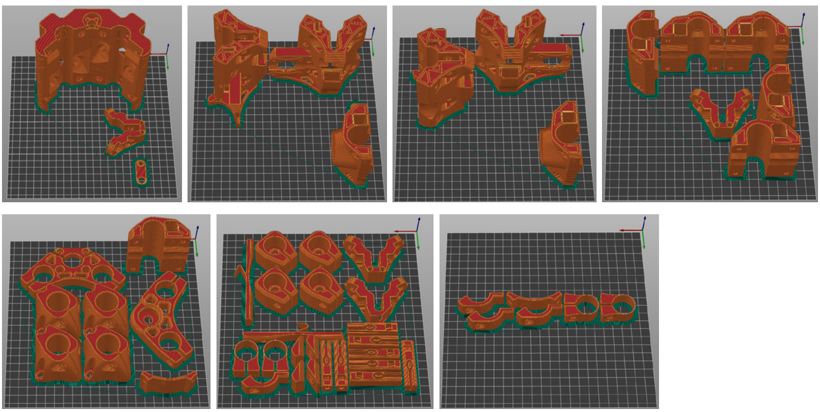

Figure 7. **Generated print jobs ID. 1 to 7 for the evaluation product MPCNC** (first row top left starting with ID1 to 4 and second row ID 5 to ID 7).

Source: Author's illustration

For the purpose of evaluation of the implemented solution, the computational time required for producing larger quantities of parts is considered. The computation time is created for the two evaluation products for the quantities of 5, 10, 20, 50 and 100 pieces and is divided into computation sections as shown in Table 5.

***Table 5.* Scaling of the number of pieces produced and their calculation time for the milling machine evaluation product** (with a maximum production time of 24 hours)

Product quantity	Quantity of print jobs	Time duration of calculations (h:mm:ss.ms)			
		Parts nesting	Transfer nesting	Slicing files	Total time
5	32	0:00:00.1	0:02:22.5	0:14:07.5	0:16:30.2
10	64	0:00:00.3	0:04:52.9	0:26:56.5	0:31:49.9
20	128	0:00:01.4	0:08:51.9	0:50:34.2	0:59:27.6
50	318	0:00:07.5	0:21:51.1	2:16:47.1	2:38:46.5
100	638	0:00:28.8	0:44:49.4	4:32:45.7	5:18:05.7

Source: Author's illustration

As the calculation time measurement for the previous print job generation has shown, the procedure of the transfer from the nesting algorithm to the 3D model placement and slicing is by far the most time-consuming. An optimization for this is the reuse of the already generated and sliced print jobs. For this purpose, after the theoretical print jobs have been created in compliance with the time duration and the nesting run, it is checked whether a print job has already been generated for the parts constellation of a print job. If this exists, the steps of the transfer and the slicing are omitted and the already created print job is used again. Table 6 shows the generated print jobs with the calculation time using this optimization.

***Table 6.* Scaling of production quantities with optimized computation time by reusing generated print jobs and multithreads for the evaluation product milling machine** (with maximum production time of 24 hours)

Product quantity	Quantity of print jobs	Built print jobs	Time duration of calculations (h:mm:ss.ms)			
			Parts nesting	Transfer nesting	Slicing files	Total time
5	32	18	0:00:00.1	0:00:31.9	0:05:37.9	0:06:09.9
10	64	22	0:00:00.2	0:00:44.1	0:09:24.4	0:10:08.8
20	128	29	0:00:01.0	0:00:47.2	0:11:50.0	0:12:38.3
50	318	37	0:00:06.1	0:00:55.7	0:15:55.4	0:16:51.3
100	638	37	0:00:24.4	0:00:55.7	0:15:55.4	0:17:15.6

Source: Author's illustration

5. RESEARCH RESULTS ON SYSTEM EVALUATION AND RESEARCH OUTCOMES

This chapter presents the outcomes of the implementation and evaluation of the proposed system architecture for AM integration. The developed architecture was assessed through the realization of multiple system components and their interaction in simulated production environments. The methodology for automated generation and coordination of production orders was instantiated as a multi-layer planning and control system, supporting both centralized and decentralized execution. **The key scientific contribution of this research is the time-aware utilization of build space, which serves as a computational foundation for subsequent control layers.** In addition, the architecture incorporates intelligent and decentralized extensions that enhance planning precision and coordination efficiency within cyber-physical production environments. The combination of these approaches demonstrates the practical viability of the proposed solution and its capacity to support scalable and flexible AM production within digitally integrated enterprise systems.

The evaluation of the developed architecture confirmed that the system enables a high degree of flexibility and adaptability in managing additive manufacturing resources. Simulation-based testing validated the functional completeness of the proposed modules, including order generation, scheduling, and real-time monitoring. In addition, the experiments revealed significant improvements in the utilization rate of AM equipment and the efficiency of production order generation when compared with static PPC configurations. The integration of machine-learning-based predictive models further improved the accuracy of production time estimation. Compared to static planning parameters, the ML module reduced deviations between predicted and actual build times, enabling more efficient resource allocation and greater scheduling flexibility within the AM-PPC system. The predictive component thus enhances the planning precision of the overall system, allowing it to dynamically adapt to varying workloads and process constraints. These results demonstrate the feasibility of applying intelligent, data-driven models to optimize job sequencing and throughput in additive manufacturing environments. Furthermore, the blockchain implementation demonstrated its ability to synchronize production orders between multiple independent entities in a distributed network. The smart-contract approach ensured transparent execution and traceable process documentation, validating its applicability for secure order management in cyber-physical production environments. The evaluation also showed that decentralized coordination reduced manual intervention and increased the reliability of inter-organizational communication. This confirms the suitability of blockchain technology as an enabling mechanism for distributed production networks in Industry 4.0 contexts.

Practical contributions of this research and contributions to Design Science are discussed in Chapter 5. In summary, this research produced new knowledge on integration of AM into industry-scale manufacturing environment controlled by ERP systems. Specifically, new knowledge was produced for the following key stages of manufacturing process involving AM: creation of production orders; forecasting of production times; and utilization of resources in a decentralized production network.

CONCLUSIONS

In this dissertation, the following *research thesis* was put forward for the defense: *the industry-scale introduction of Additive Manufacturing (AM) in the manufacturing environment established by Traditional Manufacturing Technologies (TMT) can be enabled with the development of appropriate process management and process control solutions*

This thesis can be considered as proven true, given that the overarching research task was fulfilled, and *a software architecture was proposed, developed and evaluated, to allow AM-specific Production Planning and Control (PPC) and its integration with the traditional Enterprise Production Systems (EPS).*

Additional conclusions can be drawn based on the knowledge obtained though the research presented in this dissertation:

1. The integration of AM into existing production systems requires overcoming architectural incompatibilities between AM process characteristics and the embedded control logic of traditional ERP systems. These systems are optimized for high volume, low variability environments and do not natively support the dynamic and customized nature of AM workflows.
2. A comparative analysis of traditional PPC logic and AM process characteristics reveals concrete gaps in system behavior, data integration, and process coordination. These gaps necessitate the development of new computational models and architectural elements for hybrid PPC environments that include both TMT and AM.
3. Existing research in AM has focused predominantly on process level optimization and machine level control. Little work addresses the integration of AM into full scale production environments governed by enterprise IS. This dissertation demonstrates the need for a comprehensive, structured multi-layer system architecture tailored to AM integration into enterprise-scale CPPS.
4. The proposed system design draws on domain knowledge of traditional production environments and extends it to accommodate the distinctive requirements of AM. Key considerations include build process modeling, time-oriented scheduling, decentralized coordination, and predictive resource allocation.
5. The inherent limitations of AM for high volume production such as long cycle times and resource intensive post processing, can be mitigated through different optimization techniques: efficient nesting of multiple print jobs, dynamic scheduling based on predicted completion times, and intelligent allocation of distributed production resources.

6. AM, when integrated into a hybrid environment with TMT, increases production flexibility, responsiveness, and the ability to support mass customization across the production chain, and opens up new opportunities for scalable AM deployment and system level innovation in digital manufacturing. For example, characteristics previously viewed as drawbacks, such as long print durations, can be leveraged as architectural and organizational innovations: rethinking resource shifts, planning windows, and hybrid production strategies.
7. Effective implementation of AM in enterprise systems requires expertise not only in production processes, but also in the configuration, extension, and coordination of complex IS. The ability to map physical operations into digital workflows is central to this challenge.
8. The digitization required for AM integration introduces new challenges and opportunities in data handling, including real time coordination, process transparency, and the management of large-scale manufacturing data. These topics are central to the broader goals of Industry 4.0.
9. This dissertation shows that disruptive technologies can be integrated into existing production architectures without abandoning the established control principles of traditional manufacturing. Through carefully designed system components, AM can complement traditional processes rather than replacing them entirely.
10. The Design Science Research Methodology has proven to be an effective paradigm for developing solution-oriented artifacts that address architectural and computational challenges in modern production systems.
11. The contributions of this work, including models, constructs, optimization methods, and integration logic, offer a validated and generalizable foundation for future research and system development in hybrid production environments that combine traditional and AM technologies.

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