Development of an Automated and Continuous Data Extraction and Input Pipeline in AM for Simulation Processes using Ontology-Based Knowledge

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Abstract

Additive manufacturing (AM) known as rapid prototyping or 3D (three dimensional) printing, has been widely applied to multiple industrial domains to address supply chain (SC) disruption issues caused by crises, such as COVID-19. The significant benefits of AM have been proven in a substantial number of current research studies. However, the adoption of AM in SC, which would also enhance and maintain SC performance, still lacks focus. Meanwhile simulation has been identified as a powerful tool for mimicking and predicting processes by executing numerous scenario setups. However, the challenge remains in the manual operation of the simulation process, whereby operators normally input hundreds, if not thousands, of scenario datasets each time for execution. This paper aims to propose an automation process for simulation using the ontology-based database from the AM and SC ontology combination. The network optimisation model for AM SC is modelled using two simulators (Anylogistix and Tecnomatix Plant Simulation), thus formulating an automated data pipeline between simulation and knowledge base.

Keywords: Data pipeline, Automated simulation process, Plant simulation, Anylogistix, Ontology, Knowledge graph

1 Introduction

The fast-approaching technical developments in the manufacturing industry and communication technology are going to change traditional business models. Digital services as part of platform economy ecosystems can cause a significant transformation of these models. This is because there is now a better understanding of the needs and benefits of these fundamental technological changes [1]. It is now essential to focus on the customer needs in terms of the usefulness and efficiency of the underlying tasks and processes for this transformation [2].

With a holistic view on the additive manufacturing (AM) supply chain (SC) it becomes clear that – subdivided to the most granular manageable level – this AM SC is a network of roles and capabilities that must be orchestrated effectively to fulfil customer needs and outperform existing technologies. Due to the variety of customer needs, these networks can be adjusted according to performance goals, whether to be more economic, resilient or ecological [3].

In addition to this selection of specific aspects of suppliers in SCs, decisions should also take into account logistics as the interconnection between each process node. These decisions can be derived from the traditional 6-Rights of Logistics, or considering more dimensions such as information, packaging or ecological footprint [4].

Referring to these described challenges, an increase in the degree of data integration and interoperability along the AM SC could lead to certain improvements. This leads to a research question that should be answered using multiple case studies.

RQ: How can the data in AM SC be formalized in a common data framework to support a simulation-based performance assessment?

2 State of the Art

2.1 Simulation in AM SC

Using simulation methodology plays an essential role in the context of the AM supply, mainly because it has the potential to optimize processes and enhance

performance. Numerous studies have investigated the amalgamation of design for AM and SC design, revealing that the additional capabilities of AM can improve SC performance in terms of lead time and total cost. For instance, Chiu and Lin proposed a simulation-based method to evaluate the effects of demand variability and stochastic demand on customized items, showing how AM can enhance the flexibility and resilience of SCs [5]. Similarly, Zhang et al. discovered that AM may not always reduce costs, but it offers substantial benefits for specialised spare parts in low demand [6]. Their study demonstrates that 3D printing can be a viable option in certain operational scenarios by reducing the need for warehouses and expenses.

Another example of a study that approached simulation in an AM SC context is presented by Essig et al., which examined the influence of AM on SC resilience during emergencies, including the COVID-19 pandemic and the Suez Canal obstruction [7]. The research simulated a healthcare SC and determined that AM designs, mainly dispersed manufacturing models, might sustain elevated levels of availability and alleviate risks linked to supply disruptions. This shows how AM can be integrated into risk management frameworks for SCs. Hence, simulating the complexities of the AM SC can help to figure out bottlenecks, evaluate risks, and discover opportunities to save costs. It enables companies to test various production setups, distribution methods, and demand predictions in a digital environment, thereby reducing disruptions and enhancing SC resilience.

Even though simulation has many benefits, previous research has shown that the models include a limited number of variables and do not fully reflect the complexity of SCs, especially when it comes to demand variability and the logistics of different configurations. In this context, AI technologies have the potential to overcome these limitations by optimising functions such as demand prediction and process enhancement, helping businesses to maximise the benefits of AM [8]. Integrating AI with discrete-event simulations empowers the creation of adaptive models that adjust production and distribution configurations in real-time according to variations in operational variables [9]. In addition, Melnyk et al. contend that integrating AI with simulation mitigates difficulties, including uncertainty, transient response, and causality analysis, promoting more resilient and adaptive solutions for SC management [10]. Thus, the integration of AI and simulation optimises existing configurations and creates dynamic, adaptive models that are well-equipped to handle uncertainties and complexities, thereby unlocking the full potential of AM in SC management. However, there is still the challenge of adequately integrating [11].

2.2 Semantic modelling in AM SC

The importance of data exchange in SC management has been extensively researched, with numerous studies examining this subject. Regarding the industry-wide data sharing in automotive domain, Legenvre and Hameri have shown that sharing data across SC is becoming increasingly important for many companies [12]. This has led to the need for a digital infrastructure for data sharing in the automotive industry. In another research, Ramayah and Roaimah examined the role of information in operational and strategic level exchange in SC performance, concluding that strategic information shared between SC partners significantly impacts SC performance [13]. In the AM SC domain, the one-step production method results in a substantial increase in data exchange between supplier, manufacturer and customers [14]. Previous research has also investigated the partner selection process in AM SC, which involves multi-criteria related to AM adding value processes of different SC roles [3]. The necessity to formulate a high-interoperable and highly responsive supply network of AM also demands a high level of information exchange and integration [14]. Information is exchanged not only between the different stakeholders (manufacturer, demander, and community) but also between the different stakeholders and network coordination.

Data interoperability in SC management is considered critical to a successful digital interoperable SC. However, the challenges that hinder the interoperability of data management in SCs can be categorised as follows: namely, the lack of an effective and open inter-organisational data sharing format, weak data communication, privacy and security concerns, and the standard of product/order-oriented data [15]. Among these barriers, the lack of an effective and open inter-organisational data sharing format is considered to be the most significant. To overcome this issue, a common use of data standards and shared understanding of data plays a decisive role.

Semantic modelling has been proved to be useful in the context of SC data sharing, through the integration and interoperability of data from different sources, thereby facilitating a shared understanding of the exchanged data. The utilisation of semantic modelling models based on ontology technology helps resolve semantic heterogeneity and provides a common understanding of the key concepts in SC management [16]. Additionally, a Semantic Web SC model has been developed to analyse SC collaboration based on the ontology-based model, thereby enhancing the collaboration degree among SC partners [17].

Knowledge Graph (KG) was recently developed after the introduction of Ontology Web Language (OWL) in 2004 and Linked Open Data in 2007 to facilitate the

compelling abstraction process for organising the world's structured knowledge and for integrating information extracted from multiple data sources [11]. The main components of the KG include (1) nodes and (2) edges. Nodes represent world entities, such as people, companies, and organisations, while edges describe the relationships between them. Due to this entity-relations structure, each smallest unit in a KG has a triple format, representing the Subject (S), who/which generates the relationship (R) to/with the according Object (O). Applying this concept to the AM SC database, the entity in KG reflects the stakeholders, organisations, companies, individuals, resources and the edges carry the relations between these components, which provide us with a completed and organisational architecture of the AM SC model.

3 Framework development

3.1 AM SC Data requirements

The development of the described framework is based on an analysis of processes and process chains in the field of AM, with the objective being to utilise simulation models to facilitate the generation of well-founded and precise cost and time estimates for the manufacture of products. A variety of approaches for estimating manufacturing costs and time have been proposed in the literature, which differ in terms of the effort and accuracy required. A comprehensive classification of these approaches can be found in [18], in which existing methods are categorized into qualitative and quantitative approaches.

In this paper, the focus is on the application of quantitative methods. Among the methods examined, the analytical method demonstrates the highest level of accuracy. However, this method also requires the greatest degree of effort, since the necessary parameters must be determined through a detailed investigation of the specific AM process, the product and the production system.

The basis of this method is the decomposition of the product's process chain into individual components, with the resources required in each case being evaluated. The estimation of costs and time is based on the aggregation of the costs of the resources used to manufacture the product. [18–20]

This process-oriented approach is based on the ISO/ASTM 52920 standard, which provides a systematic representation of all processes relevant to AM [21]. The process chain considered refers exclusively to the production of an additively manufactured part. However, to enable a holistic view of the value chain, additional relevant steps were included (Figure 1).

As part of a comprehensive literature review, the individual process steps were analysed, and relevant parameters and dependencies were identified. This analysis resulted in the development of a data structure that serves as the basis for developing the simulation models. An exemplary step in this process was the identification of the relevant cost types, which were classified into three principal categories along the process chain: costs prior to the manufacturing process (pre-process), costs during the manufacturing process (print-process) and costs after the manufacturing process (post-process). The systematic collection and processing of this data enabled the essential parameters for the cost calculation model to be determined.

The input data and configurations of the AM chain are subject to constant change due to the individualised order structure and the dynamic innovation development in this area. This necessitates the continuous adaptation of the relevant input parameters. Consequently, an ontology-based approach was selected to structure the data, thereby enabling the retrieval of requisite data from a KG via an interface and its integration into the simulation model. This approach offers the advantage of enabling regular updates to the ontology and KG, thus facilitating the incorporation of new data. This facilitates the development of feature-sets for specific investigative

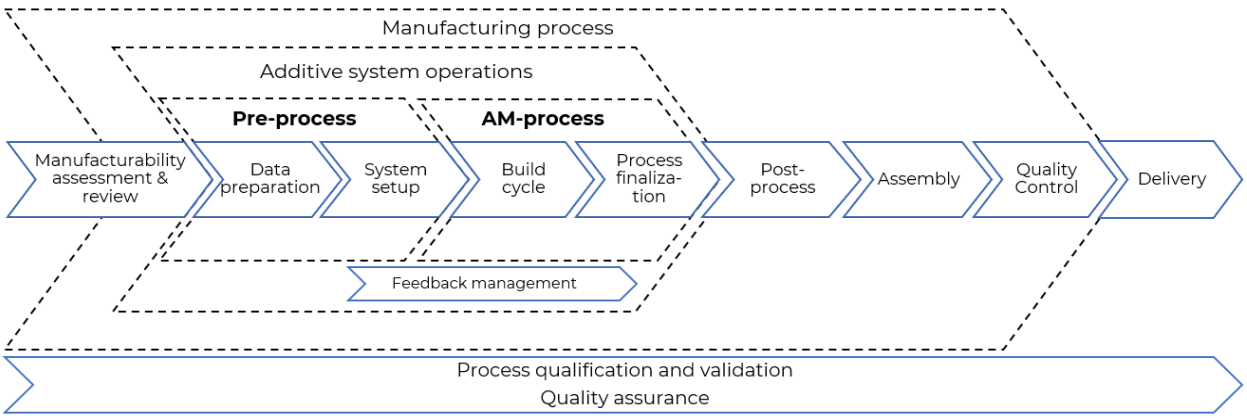

Figure 1: Overview on End-to-End process chain AM in conjunction with ISO/ASTM 52920:2023

purposes, particularly in the context of the ongoing advancement of simulation use cases in SC [11].

3.2 Framework Design

The framework design was developed using a Systems Engineering approach in order to couple the simulation with other systems [22]. The aims of this coupling are the automation of the process of simulation generation and prediction of multiple scenarios.

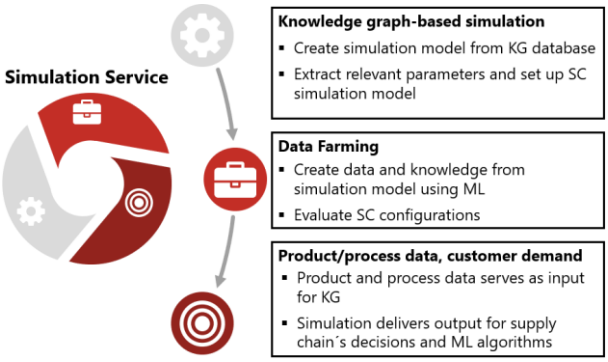

Figure 2: Approach for coupling simulation and ML [22]

The simulation is used to model the AM supply chain and provide possible outputs from predefined conditions. In contrast, the ML is expected to generate different simulation scenarios based on historical data (training data). This concept emphasises the process of retrieving data from expandable databases and standard data from various sources. Figure 2 describes the concept, which includes three components: (1) KG-based simulation, (2) data farming process, and (3) product/process data. As this represents a generic approach, specific case studies were conducted with the aim of defining the scope, objectives and the needs of the system by the means of the framework [23].

3.2.1 AM Network Optimisation (Anylogistix)

In order to develop a model for network optimisation purposes, our research team decided to adopt the Network Optimisation Model (NOM) of Anylogistix as a tool for modelling a specific test case at SC level. In the test case that was designed for this study, an order for an AM product with 1000 units was analysed. These units belonged to three different customers (two in Germany and one in France). The aim of the network configuration model technique is to propose the most optimal network option based on minimizing overall cost [MIM25]. The NOM has been executed 1000 times to figure out the optimal solution, which leads to a set of required information points, and the network of supply can be seen in Figure 3.

The model has been executed, resulting in a set of required data points for the NOM in Anylogistix. These data points can subsequently be mapped to the

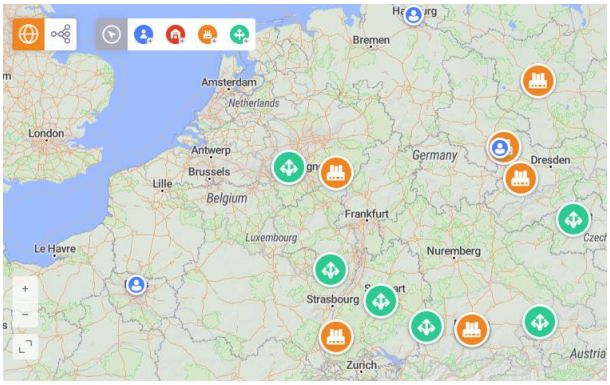

Figure 3: NOM of the test case in Anylogistix

ontology-based KG for automated querying and modelling. The necessary data points, their respective data formats and their sources have been documented and used as guidelines for the interface data structure between simulator and KG.

The test case under consideration resembles a typical cross-border AM SC, with customers (blue) located in Hamburg, Leipzig and Paris, and production facilities (orange) spread across Europe, in addition to distribution centres (green). With regard to the end-to-end process chain, these centres can assume the roles of post-processing, assembly and/or quality control. A typical question in this context is where to optimally locate the distribution centre, given demands from customers, production and logistics capacities. This optimum may rely on multiple criteria, such as the maximisation of profit, the minimisation of lead times, and the minimisation of inventory costs. It may also take into account the means of transportation, for example.

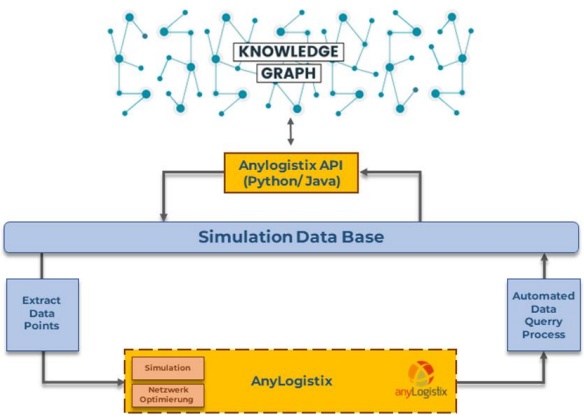

Figure 4: Data flow between Anylogistix and ontology-based database

Figure 4 shows the interaction between KG, Simulation Data Base – as a data-wrapper – and the Anylogistix functions itself. This approach helped to analyse the different features of SC-Analysis with a specific software and determine a base set of necessary data and features.

The Anylogistix simulation environment itself comes with several APIs, either for the automation of the simulation runs and their controls, or to access other services such as mapping and routing to create simulation models based on real-world driveways between different partners of the SC. Therefore, the data needs can be reduced to an essential minimum for each partner, such as the types of roles that can be fulfilled in the SC, geographical locations as coordinates and their capacities, for example.

3.2.2 AM Production System Simulation (Plant Simulation)

To simulate production processes effectively, we employ discrete event simulation (DES). However, conventional DES tools, such as Tecnomatix Plant Simulation, typically focus on modelling production systems at the factory level, often neglecting the broader context of the entire procurement and SC. In order to address this limitation, an integrated approach has been developed that extends the capabilities of Tecnomatix Plant Simulation to model production systems up to the SC level.

The primary aim of this extended simulation approach is to estimate critical production metrics, including production cost, production time, and product quality, specifically within the AM SC. This integrated simulation framework provides a comprehensive analysis that facilitates informed decision-making throughout the production process. By modelling the entire production chain from start to finish, the simulation enables detailed evaluation of performance. Predefined production scenarios, as well as scenarios generated by Python scripts and optimised through genetic algorithms, are employed to simulate the production process. The system returns key performance indicators (KPIs) that are essential for assessing overall system performance. Figure 5 shows how different estimation models are integrated in plant simulation framework.

3.3 Framework Application results

The execution of selected test cases by two distinct simulators (Anylogistix and Tecnomatix Plant Simulation) has resulted in the establishment of a framework that describes the data flow between ontology-based knowledge (KG) and the interface of the simulation database. While the data format of KG is defined as turtle with the triple format, the input and output from different simulators include different formats of data. This necessitates interpretation of the standard simulation data and KG data but offers the independent development of these modules and easy exchange of features. A data mapping process is then required. In this data mapping process, our team adopted a data pipeline tool called CMEM from eccenca [1], which enables mapping of data from multiple sources and formats to data points in the KG (Figure 6).

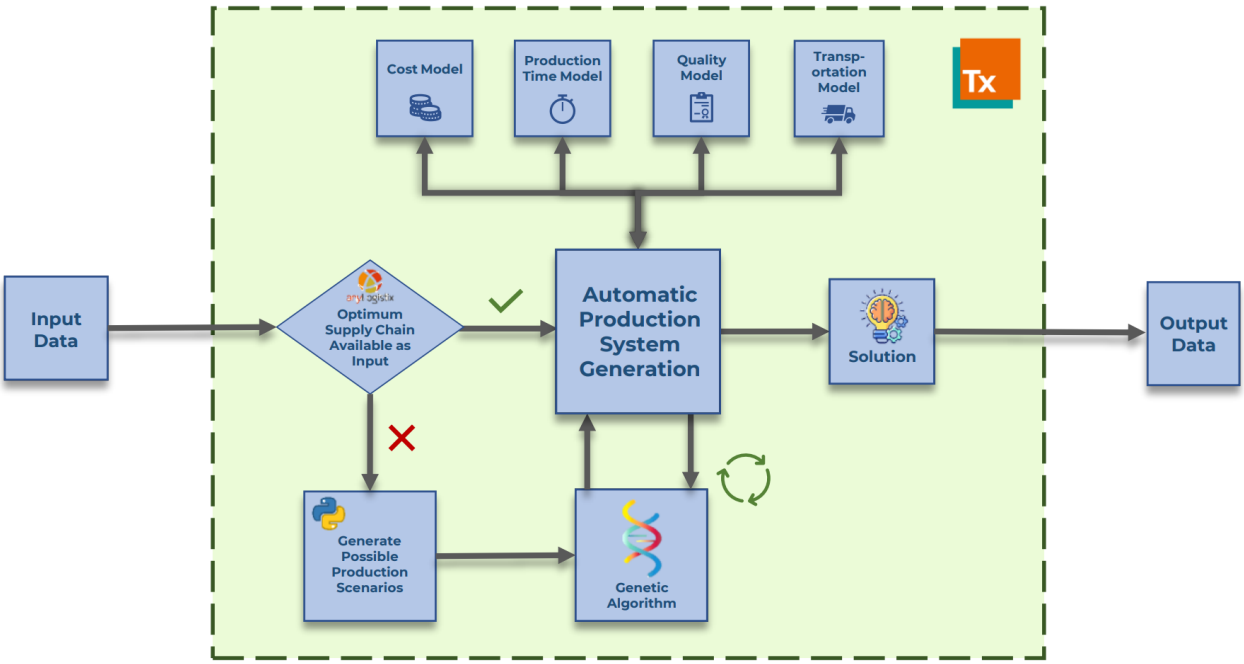

Figure 5: Data Flow and modules in the Production System Simulation with Tecnomatix Plant Simulation

[1] Enterprise Knowledge Graph Solutions: https://eccenca.com/

One of the great advantages of using semantic modelling database in this case are (1) extendable feature, and (2) semantic understanding between different stakeholders. This means that additional data can be added to the KG structure during the simulation process, creating a new data point for future use. The common understanding of semantic modelling allows multiple simulators/operators to share the same labels for data points. These two features enhance the standardisation and flexibility of the simulation database, which is considered important in the context of a simulation service for an AM SC platform.

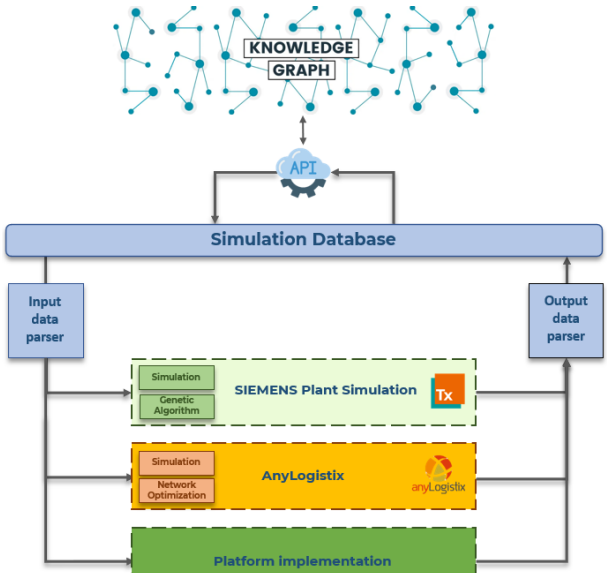

Figure 6: Overall data pipeline between simulators and ontology-based KG

4 Conclusion

The paper provides insight into the requirements and realisation of an automated data pipeline between an ontology-based data model (KG) and different simulation environments, by executing expert-based case studies of AM products. While Tecnomatix Plant Simulation uses DES for simulation of the production process, Anylogistix provides an abstract view on the network design between suppliers (including manufacturers, logistics service, and non-printing item providers) and customers (located in different geographical areas in Europe). It is anticipated that the case study will provide valuable insights into the automation process of the simulation, with a particular focus on the data querying operations of different scenarios. These operations are currently performed manually, which results in a significant expenditure of time and effort, particularly in scenarios where a high volume of simulations is required.

Additionally, the utilisation of semantic data modelling as database architecture brings the concept of adaptable and extendable databases for AM SC simulation closer to the operational level. With the ability to store expert knowledge inside the KG, the graph database in this case aims to function as a knowledge carrier for this application field, so that similar domain problems can be adopted.

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