Concept Development for Coupling Simulation and Machine Learning in Supply Chains

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Abstract. This study provides insights into the development of a combined simulation and machine learning approach in the field of additive manufacturing (AM).
The systems engineering (SE) methodology is used to determine the relationship between different engineering objectives in the area of semantic supply chain modelling to validate the results of a matchmaking model for the digital AM supply platform to increase its network resilience. The concept is used as a basis for further implementation.

Introduction

The aim of this study is to present the current state of research on the coupling of simulation and machine learning (ML) in the supply chain environment as part of a research project to create a platform-based simulation service.
During the last year, several prerequisites have been elaborated, one of which is the possible coupling scenarios for simulation and ML [1]. From four cases based on VDI 3633 Part 12:2020, the combination of simulation followed by a ML approach was selected as the basis for further investigation. [2].

In addition, the different approaches to determining the resilience of a supply chain have been examined by Grzona et al. [3].

Based on the literature review, different use cases were identified and the targets for the simulation studies. Time and cost were the most mentioned objectives for investigation in the literature and the use of reinforcement learning and neural networks as ML's techniques of ML. The survey also identified the possibility of increasing the ML knowledge of simulation experts.

1 Methodology

The research objective to be achieved is to create a concept for the coupling of simulation and ML in an exemplary value network to assess the previously mentioned objectives.

This leads to two Research Questions (RQ):

- RQ1: What can an exemplaric value network look like?
- RQ2: How can a coupling concept look like?

An SE approach was chosen to further develop the concept for the implementation of the coupling case. The SE approach is a well-established methodology for designing systems that incorporates the principles of systems thinking.

The SE process model and the methods and tools used in the problem-solving process support a systematic transfer from an actual state to a desired state.

Understanding the elements and relationships within the system and their relationships to the environment and environmental systems is a fundamental aspect of systems thinking. [4]

These systematic perspectives can also be used in conjunction with technical systems in socio-technical systems, which incorporate human and societal aspects [5]. In addition, the entire lifecycle of a system is considered, from its development to its realisation and use [4].

2 Concept Development

Ahrens [5] proposed a six phase approach for an SE cycle (Figure 1). As the scope of the design is determined by the project, a brief introduction will be given, followed by an explanation of the connection to the matchmaking process. This is followed by a description of the technical objectives that lead to the methods used to produce the overall concept in the penultimate step.

2.1 Reasons for the design project

The aim of the project is to develop a digital platform for AM to increase the resilience of value networks using artificial intelligence and ontologies.

Since the data of the system elements - in this case AM resources - are based on the semantic data model, it is necessary to integrate these concepts into the overall process [6].

The AM process chain has five phases, each with its own tools, models and methodological requirements. Product design aims to create a digital object using Computer Aided Design (CAD) software.

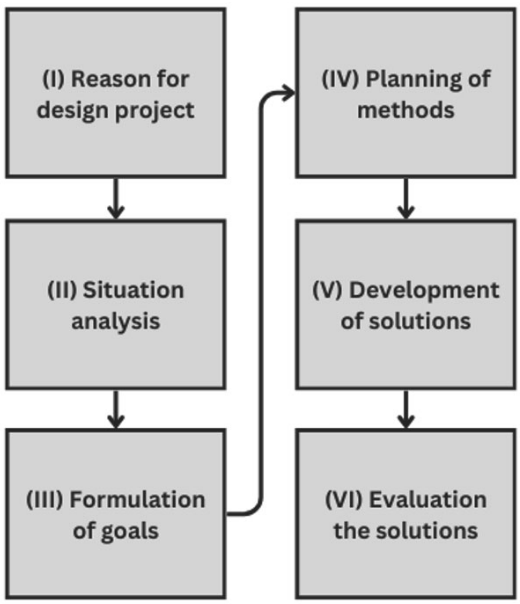

Figure 1: Six phases of SE process according to Ahrens [5].

The pre-process is typically done in Computer Aided Planning (CAP) software to optimise the build space, slice the model and set the machine parameters.

During the printing process, several measures are taken to monitor the build process and, if necessary, adjust the machine parameters on the fly to reduce the error rate. This is supported by Computer Aided Manufacturing (CAM) software. After printing, post-processing typically involves a number of steps, including cleaning and separation of the support structures and verification of the physical product and process dimensions.

The final stage is the finishing process, which uses a combination of techniques, including thermal finishing to harden the products, mechanical methods and quality control, which may be destructive or non-destructive. Each of these steps takes a certain amount of time [7].

2.2 Situation analysis

The Simulation/ML core should be used to validate and support the general matchmaking process on the platform [8]. This is driven by the semantic data model for the capabilities of the different roles in the process chains.

Out of the process chain, a graph is generated for the value network, which requires multiple combinations of suppliers and partners to be found using a matchmaking service.

At this stage, the behaviour of the network is not evaluated or assessed in terms of resilience, time, price, or quality. These are then used to develop the models for the Simulation/ML.

2.3 Formulation of goals

The technical goals were elaborated in a continuous group work process. As previously mentioned, a semantic database is required. For this project, a specific AM logistics ontology was employed, which is connected to the AM ontology [6].

As the concept needed to be proven first, the focus was on incorporating existing simulation tools rather than developing new ones. Therefore, Siemens Tecnomatix Plant Simulation, AnyLogic, and Anylogistix were chosen for their ability to interact with external software through interfaces.

In addition to working with these tools, the solution should be capable of analysing data from multiple simulation experiments. This will provide a data basis for determining whether a reinforcement learning or neural network approach can be used.

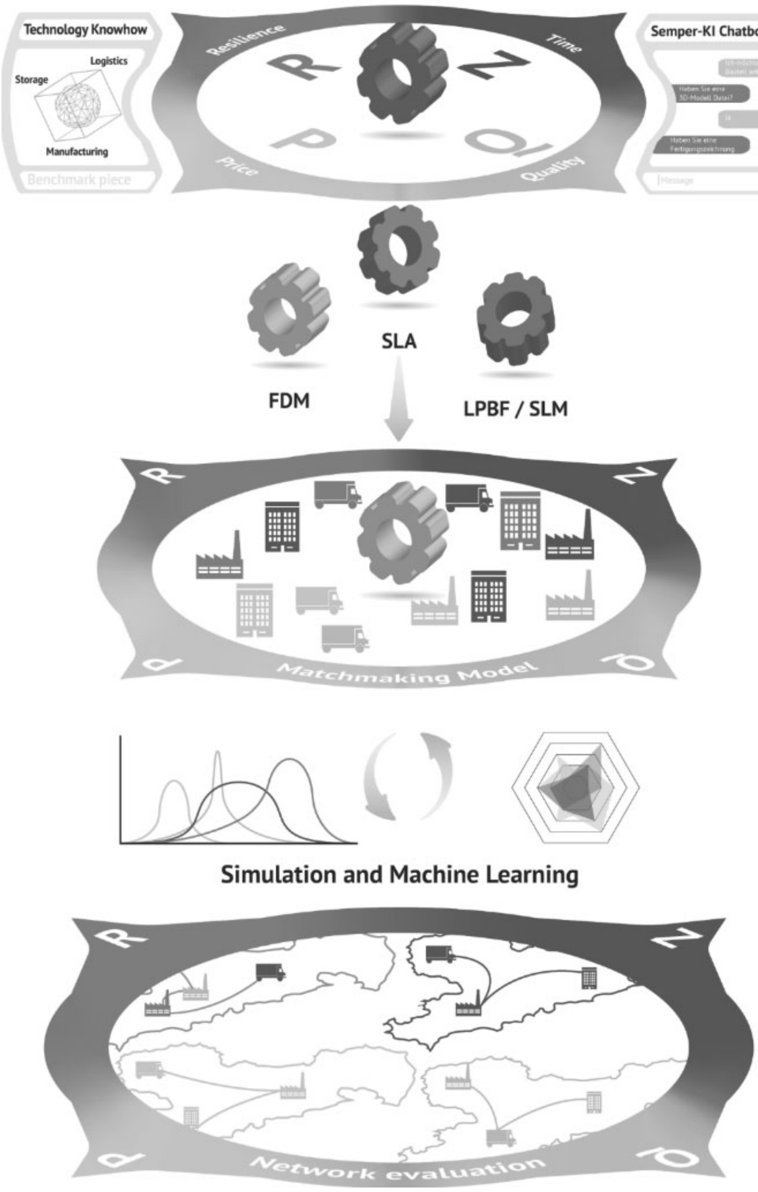

Figure 2: Meta model of matchmaking model and Simulation/ML core © InfAI e.V. Leipzig.

Due to the involvement of stakeholders from various domains with differing levels of expertise, the development of a highly comprehensive model is essential. Initially, the model should address time and cost, with the flexibility to adapt to additional aspects as required.

2.4 Planning of methods

For the problem-solving cycle, the case study method was selected because of the exploratory and unique nature of the problem to be solved. [9].

The first test case was defined based on a product consisting of three different parts, manufactured by the three partners and delivered to one customer. It is important to note that the partners have different production capabilities, and that the product requires a number of steps of post-processing. These steps consist of refining the parts, assembly, quality control, packaging, and delivery to the customer.

2.5 Development of the solution

The concept pipeline has been developed (Figure 3) to meet the previously outlined requirements. To connect the different systems, KNIME, an open-source and versatile data mining tool, is used. In parallel, it allows for the use of ML techniques and fulfils the node-oriented interface design goals.

In order to provide a precise answer regarding the lead time, it is necessary to consider the specific capabilities of our partners, their geographical location, and the processing times.

This can be evaluated using Anylogistix in the experiments. The various AM technologies have a considerable impact.

For instance, the powder bed fusion process has different optimisation criteria compared to a fused deposition modelling process in terms of the use of building space and the number of parts produced in parallel [10].

With regard to the cost assumption, it was necessary to evaluate not only the time required for printing, but also to consider the various resource costs in the network and the relationships between them [11]. This resulted in a partner and activity-based cost formula for each subject in the value network. The solution was developed by one currently self-defined case, which follows the assumption that each partner could have multiple roles in the supply chain.

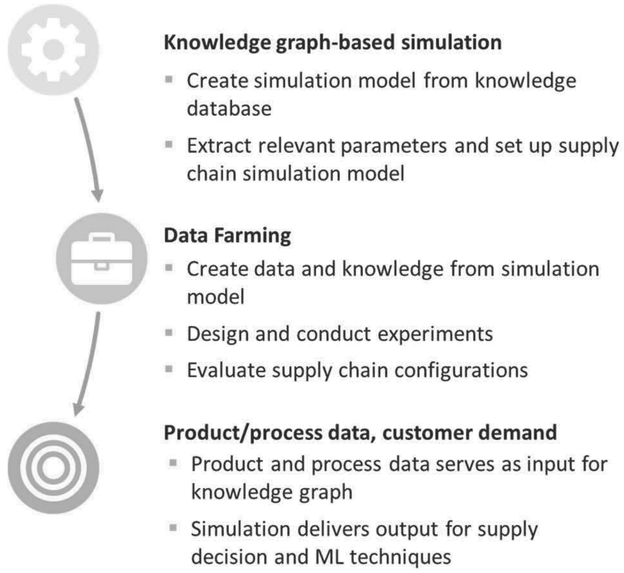

Figure 3: Pipeline for Simulation/ML ©Fraunhofer IWU, Chemnitz.

This role model can be understood on the ontological level as domain-specific knowledge. Additionally, the knowledge for the specific value network is represented by the knowledge graph derived from the database and used by the simulation software.

The results are then transferred back to the knowledge graph on the platform. This data will then be used to train the ML algorithms.

2.6 Evaluation

Due to the inherent characteristics of the SE process, it was not possible to fully evaluate the results at the system level; instead, the evaluation was carried out at the level of the system components.

The simulation will be run using both simulation tools connected to the KNIME data flow model, and their results will be compared to a deterministic model of the value network. The results of the deterministic model will then be recalculated with classic spreadsheet software to validate the gained solutions.

3 Conclusion and Limitations

The research questions have been addressed, and the concept has been proven in part with only one case study, which only includes manufactured parts.

Further evaluation is required with different and more complex value networks. The study provides an overview of a data-driven platform's overall data flow process involving simulation techniques.

Additionally, the use of slicing software such as Slic3r or hardware-specific tools is recommended to more accurately estimate the in-process time. As the data backend is not yet fully available, the data stream as input was manually added, so the amount of data is not yet sufficient to run ML techniques in a meaningful way. This necessitates further incorporation of the knowledge graph stack in a proof-of-concept stage.

This will also lead to further investigations to assess which type of ML technique is more suitable for the connection with the simulation tools used. Due to the project's characteristics, no difference or performance comparison with other approaches is made, which would provide more insight into possible performance or quality advantages at the decision level.

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