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Requirements for a ML- and Platform-based Simulation Service

Anforderungen für einen ML- und plattformgestützten Simulationsservice

Pierre Grzona, Technische Universität Chemnitz, Professur Fabrikplanung und Intralogistik, Chemnitz (Germany), pierre.grzona@mb.tu-chemnitz.de

Mai Thi Yen, Westsächsische Hochschule Zwickau, Fakultät Wirtschaftswissenschaften, Zwickau (Germany), yen.mai.thi@fh-zwickau.de

Florian Zumpe, Fraunhofer-Institut für Werkzeugmaschinen und Umformtechnik IWU, Chemnitz (Germany), florian.zumpe@iwu.fraunhofer.de

Marc Münnich, Fraunhofer-Institut für Werkzeugmaschinen und Umformtechnik IWU, Chemnitz (Germany), marc.muennich@iwu.fraunhofer.de

Abstract: Today, with the rapid development of new technologies, many industries have adopted them to enhance their performance. Among them, additive manufacturing is known as a rapid manufacturing process that can produce products in a single step, reducing time to market. Since 2019, COVID-19 has caused significant negative impacts on the global supply chain (SC), including shortages of medical goods. Therefore, an agile and flexible medical SC is required. While machine learning (ML) methods are known for using big data to gain valuable insights through forecasting, simulation enables unlimited if-then scenarios to make informed decisions in optimising SC operations. The combination methods between ML and simulation in solving SC issues has not been investigated at a sufficient level. This paper, therefore, aims to explore the advantages of coupling ML with simulation techniques in the SC field by conducting a systematic literature review. Through an expert survey, requirements for a ML and platform-based simulation service will be investigated from a technical point of view to develop a suitable use case in the future.

1 Introduction

During and after the COVID-19 pandemic, the global SC was unable to show its resilience under high uncertainty and volatile circumstances (Durugbo and Al-Balushi, 2022). Existing digital collaboration networks could only contribute to a limited extent to the creation of new value networks in times of crisis and did not have the functionality and intelligence to move directly from acute emergencies (e.g., medical products) to production and distribution. Therefore, the question of SC resilience has recently become a frequently investigated topic. At the same time, ML and simulation techniques have been well-known for their manifold applications in multiple domains. The leverage of data in solving problems related to the SC field is also increasingly focused on by academic and industrial bodies. Especially in an uncertain environment, the sustainability and resilience of SC can be improved by using emerging technologies based mainly on data-driven methods (Kazancoglu et al., 2023). Therefore, this paper focuses on answering the question of how the combination of ML and simulation can benefit the SC domain.

Initially, a review of resilient SC approaches are conducted to formulate the concrete research questions for the paper. Based on this, a systematic literature review of ML and simulation applications in the context of SC is conducted. Research questions are then derived and subsequently answered by conducting an online survey with domain experts. The responses from the survey are analysed using the Analytic Hierarchical Process (AHP) assessment method. Finally, the results from the survey analysis and its limitations will be presented and discussed. An outlook on further work will be given afterwards.

2 Resilient SC review and problem statement

2.1 Resilient SC approaches

During the last COVID-19 pandemic, multiple SC models and approaches were developed and employed to enhance the resilience of SC network. By Jain et al. (2017) and Belhadi et al. (2021), SC resilience refers to the supply chain's adaptive capacity to deal with the disruptive event and to swiftly regain its previous performance level. Durugbo and Al-Balushi (2022) reviewed 250 journals from 1996 to 2021, and explored four dimensions of SC management strategies to deal with crises are (1) crisis supplies with essential services, (2) timely response with recovery, (3) safety with security, and (4) traceability with transparency. Also, in Burgos and Ivanov (2021), the resilience of SC during a crisis scenario has been emphasized via a case study of a food retail SC in the COVID-19 pandemic. Noticeably, this study developed and used a discrete-event simulation (DES) model to examine SC operations and performance dynamics with the help of anyLogistix digital SC. With an exploratory review of 162 papers from the SCOPUS database, Naz et al. (2022) figure out that the resiliency of SC has attracted researchers to overcome the risks and disruptions to reach successful project management post COVID-19. In this study, the importance of artificial intelligence (AI) usage in creating a sustainable and resilient SC has been mentioned. Regarding the resilience of SC models for crisis scenarios, various research has been investigated. Among them, Oliveira et al. (2019) indicate the metrics for resilience factors in SC network and Pavlov et al. (2018) introduce an SC resilience assessment using a hybrid fuzzy-probabilistic approach. Regarding Ivanov et al. (2023), the viability of SC network should be considered for the survivability of society in a long-term crisis. The concept of an intertwined supply network has also been introduced as an entirely interconnected SC that enables the secure provision of goods and services for society and the market. In conclusion, it is obvious that ML and simulation are not new to the SC domain. These techniques prove their worthiness and feasibility in these applied cases with the improvement of SC performance via various dimensions.

With the support of new technologies and methods, such as data-based analysis and modelling, the optimization process of SC network has significantly improved. Therefore, research to understand more about how and to what extent data-driven methods, namely ML and simulation, are applied to SC is necessary.

2.2 Problem statement

Started in June 2022, KISS (KI-gestütztes Rapid Supply Network) is a research project that focuses on creating an AI-supported semantic network platform to support the generation of new SC using rapid production strategies in turbulent market environments, e.g. due to a supply shortage of medical(-related) products in crises such as the COVID-19 pandemic (InfAI). AI-supported analyses and simulations are then supposed to determine the optimal production and SC configuration according to certain criteria and enable direct networking with producers on the platform. Therefore, the following general question is formulated:

- *How can simulation and ML be integrated into digital platforms to enhance the resilience of SC networks for additive manufacturing of medical(-related) products? (GQ 1)*

This general research question requires to review various aspects of simulation, ML learning and SC. This paper aims to understand how ML and simulation combination can be employed in to the digital platform, under these 2 sub-questions:

- *What are the applications of ML and simulation in SC? (RQ 1)*
- *How can the application of simulation and ML be estimated regarding the worthiness of the underlying task? (RQ 2)*

This paper provides the necessary basis for further investigation of the general research question. In the following section, this framework is concretised accordingly. The next section presents the research methodology.

3 Methodical approach

3.1 Systematic literature review process

To answer the first research question about simulation and ML applications in the SC field, a systematic literature review is conducted with the following reviewing protocol. The results from this review are categorized following the 9 Rights (9R) dimensions of logistics (Amount, Product/Object, Location, Time, Quality, Cost, Packaging, Information, and Ecological Footprint) that have been investigated in the previous paper (Münnich et al., 2023) and the four coupling cases according to VDI 3633 Part 12 (2020), including (I) Sequential Simulation follows ML, (II) Sequential ML follows Simulation, (III) Hierarchical ML embedded in Simulation and (IV) Hierarchical Simulation embedded in ML.

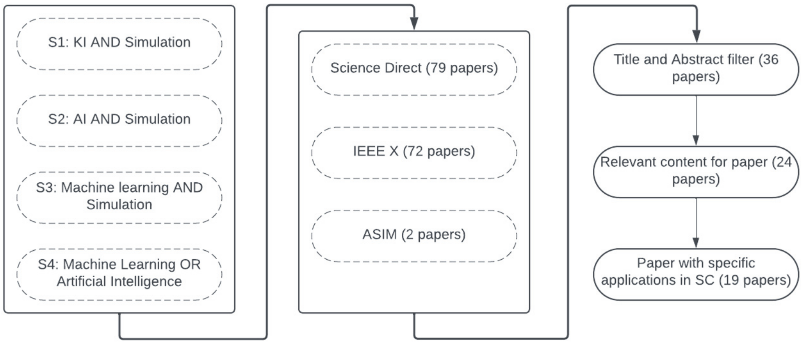

Figure 1: Systematic literature review template

3.2 Online survey

Online surveys are a tool for gaining empirical knowledge in a specific field. These could be carried out either as qualitative surveys with the help of open-ended questions (Braun et al., 2021) or as quantitative surveys with the possibility to assess probability sampling, standardized measurement and the data analysis (Fowler, 2014).

Additional characteristics of online surveys are their efficiency and economic advantages, as well as proven and stringent guidelines for their execution (van Selm and Jankowski, 2006; Punter et al., 2003). Common steps for online survey studies are Study definition, Study design, Implementation and Execution, Analysis, Discussion of results (Döring and Bortz, 2016; Punter et al., 2003).

To answer *RQ 2* a study concept was defined to determine two aspects:

- Explore the knowledge of simulation and ML from simulation specialists.
- Understand the importance of criteria to carry out either simulation or ML.

The items were transferred into a 5-level unipolar discrete rating scale questionnaire (Jonkisz et al., 2012) to assess the specific knowledge of these phases and techniques. The scale is based on the five-stage model of Dreyfus and Dreyfus (1980). It was extended by an additional category by a ‘no knowledge’-stage and the stages ‘mastery’ and ‘expertise’ were mapped in the survey category expert.

A guideline commonly used in Germany for conducting simulation studies for logistics and production systems is provided in VDI 3633 Part 1 (2014). This guideline describes a general approach for simulation studies based on Rabe et al. (2008) with separate simulation studies in several phases. These phases formed the basis for the assessment of the specific simulation knowledge. Three categories were identified to assess the level of knowledge of ML techniques. For the assessment of the coupling cases of simulation and ML, four cases were identified according to VDI 3633 Part 12 (2020) and adapted in the previous paper (Münnich et al., 2023).

The study itself was conducted with LimeSurvey. To validate the study procedure and feasibility, a pre-test was done with two experts and non-experts. The survey was initially spread at a simulation workshop conference in Magdeburg in March 2023 and later through an expert working group on simulation in production and logistics.

3.3 Analytical hierarchy process

The approach to answer *RQ 2* is based on the multi-criteria decision method of the AHP according to Saaty (1994). The goal is to obtain a weighting of the criteria for simulation and ML worthiness. The method helps with the decomposition of a problem into sub-problems and the subsequent aggregation of the partial results into an overall decision. Both rationally calculable and intuitive factors can be included in the decision-making process and quantitatively compared. The problem is mapped into a hierarchical structure and the elements (evaluation criteria and alternatives) are compared in pairs. To perform these comparisons a uniform scale is used that includes values from one (equal importance) to nine (extremely high importance), which was picked up in the questionnaire. The result of this is the assignment of certain priorities (weightings) to the evaluation criteria and alternatives. These results are aggregated, allowing the contribution of each alternative to the overall objective to be determined. The AHP was used here exclusively for weighting the criteria. A characteristic of the procedure is the integrated check of the determined weighting matrices for criteria and alternatives for their consistency. If a predefined consistency value is exceeded, the pair comparisons, the determination of the weighting vectors and the consistency check should be performed again. This leads to the reduction of wrong decisions due to potential contradictions in the evaluation. According to VDI 3633 Part 1 (2014) the simulation worthiness criteria must be considered before the simulation study. Table 1 shows the criterion for ML worthiness derived out of expert interviews.

Table 1: Criteria (only ML) for the pairwise comparison with AHP

Items	Code
Complexity of the problem, nature of the task, is this problem a recurring task?	AHP_M1
Data availability and nature How is data acquisition done, is it recurrent or is data collected only once? Are the possibilities of reference measurement available?	AHP_M2
Data complexity, is there a large number of input variables? In general, how much data is available?	AHP_M3
Exhaustion of analytical methods, are existing analytical methods exhausted or can no longer be performed efficiently?	AHP_M4
open question	text_ml

4 Study Results and Further Implication

4.1 ML and simulation coupling applications in SC

After conducting a systematic literature review with four different queries S1, S2, S3, and S4 (Figure 1), the results are presented in Table 2. Based on the review of the ML and simulation integration method from VDI 3633 Part 12 (2020), there are currently four main coupling cases between ML and simulation. This summary, therefore, collects and clusters the results according to these four coupling cases and the previously mentioned 9R dimensions of logistics.

Table 2: Current applications of ML and simulation in SC. (CC - coupling case, Sim - simulation method, DES - discrete-event, ABS - agent-based, NUM - Numerical, HY - Hybrid, RF - Reinforcement Learning, NN - Neural Networks, BDT - Boosted Decision Tree, kNN – k-Nearest-Neighbours)

Source	The Right	CC	Sim	ML Algorithm
(Illgen et al., 2020)	Time, Product	I	DES	kNN
(Azab et al., 2021)	Time, Quality	I	DES	BDT, NN
(Wojtusiak et al., 2012)	Time, Cost	III	ABS	Inferential Theory of Learning
(Bauer, 2022)	Time, Cost	II	DES	RF, kNN
(Steinbacher et al., 2022)	Time	II	ABS	RF, Deep-Q-Learning
(Nagahara et al., 2019)	Time,	I	DES	NN (RankNet, ListNet)
(Lima et al., 2022)	Ecological Footprint, Cost	III	DES	NN
(Rabe et al., 2017)	Amount, Cost	IV	DES	RF
(Nagahara et al., 2020)	Time	III	DES	NN (ListNet)
(Creighton and Nahavandi, 2002)	Time, Cost, Amount	II; III	DES	RF
(Ortiz-Barrios et al., 2023)	Time	IV	DES	Random Forest
(Vijay et al., 2022)	Time, Location, Information	III IV	DES	Coloured Petri-Nets
(AboElHassan and Yacout, 2021)	Location, Cost	III	DES	RF
(Feng et al., 2022)	Quality	II	NUM	BDT
(Bergmann et al., 2015)	Time, Information	II	DES	NN
(Qi et al., 2019)	Quality	II	NUM	NN
(Sobottka et al., 2019)	Time, Cost, Ecological Footprint	III	HY	NN
(Eriksson et al., 2022)	Time, Cost, Ecological Footprint	III	DES	Deep RF
(Pappert and Rose, 2021)	Time	II	NUM, ABS	NN

The following findings can be derived from the systematic literature review:

- DES is the dominant simulation technique used in most research.
- Production planning was the most considered application process in SC when it came to ML and simulation methods.
- The Right Time is one of the most used dimensions from the review.
- Coupling cases II and III were applied more frequently than other coupling cases.
- RF and NN are the two most popular ML techniques used in SC field.

4.2 Results of the online survey and AHP

The online survey was conducted between 7 March 2023 and 7 May 2023, 16 completed the knowledge part, including eight simulation worthiness criteria questions and five ML worthiness questions. On average, around 80% of the participants considered themselves experienced users or experts according to different phases of the simulation study by VDI 3633 Part 1 (2014). This picture turned around for ML and the coupling cases of simulation and ML. Less than 20% of the participants found themselves experienced users or experts, slightly less for the different coupling scenarios.

Figure 2 shows the results of the simulation worthiness criteria pairwise comparison and its average calculated. In total, seven participants answered the questionnaire. Two of them (P01&P05) were excluded from the average calculation (AV) because of their high consistency ratios (greater than 10%), which indicates an inconsistent result regarding randomly chosen values (Saaty, 1994). Additionally, two participants commented with an additional special requirement for visualisation and supported this with concrete scenarios.

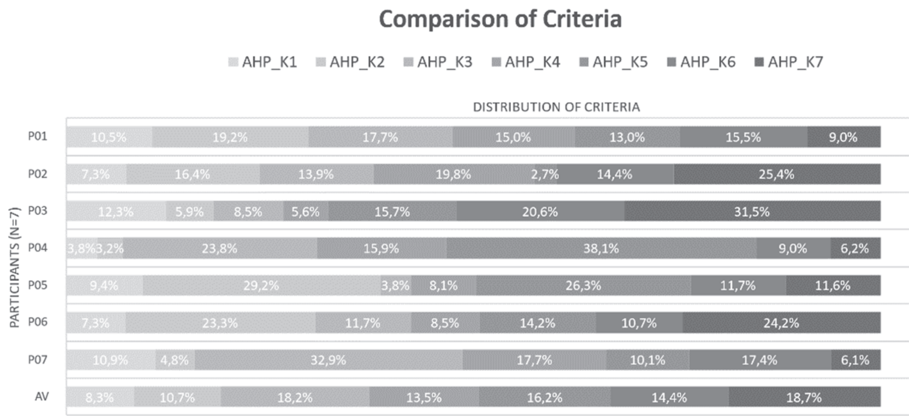

Figure 2: Analysis result of the AHP in relation to simulation worthiness

The ML worthiness criteria, on the other hand, are not presented here due to insufficient (two) numbers of complete and consistence answers.

5 Conclusion

This research result leads to the answers for the formulated *RQs* mentioned in section 2. The review of ML and simulation coupling applications in SC indicates that coupling cases II and III are the most used, with DES being the preferred simulation technique. RF and NN are the most frequently used ML techniques to improve SC performance. Many applications are related to production planning, with the goal of reducing time. Moreover, the AHP analysis revealed that all criteria are equally important for evaluation and implementation in a web-based platform service. However, there was no result for the ML criteria due to the lack of samples. Further research is required in the next phase to explore the task-oriented approach to coupling ML and simulation in SC.

Despite the valuable results obtained, there are several limitations. First of all, the limited number of samples may lead to a lack of data for the AHP analysis. Secondly, most participants in the survey had extensive simulation knowledge but little ML expertise. Therefore, assessing ML worthiness may lead to mis-interpretative results. Thirdly, ML worthiness criteria are not established by official standards but are compiled from expert knowledge. The assessment of these criteria must be dealt with in future research. Finally, like Bicalho-Hoch et al. (2022), no clear ranking of the simulation worthiness criteria could be derived from the collected data, while these criteria are highly dependent on the participant and use case.

From the conclusions of this study, several possible research directions will be considered in the next phase of the project. They include (1) improving the sample size of empirical research, (2) developing a concrete use-case for the proof of concept, (3) establishing a framework for coupling simulation and ML to enhance the SC resilience.

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