Combined Integration of Simulation and Machine Learning in a Design Methodology for Agile Production Networks

Willian Vent*, Markus Rabe#

Department IT in Production and Logistics, Technical University of Dortmund, Leonhard-Euler-Str. 5, 44227 Dortmund, Germany; *Willian.Vent@tu-dortmund.de, #Markus.Rabe@tu-dortmund.de

SNE 34(3), 2024, 167-170, DOI: 10.11128/sne.34.sn.10699
Selected EUROSIM 2023 Proceedings Publication: 2024-06-18
Received Revised Improved: 2024-07-22; Accepted: 2024-07-20
SNE - Simulation Notes Europe, ARGESIM Publisher Vienna
ISSN Print 2305-9974, Online 2306-0271, www.sne-journal.org

Abstract. An agile production network enables companies to respond quickly and economically efficiently to expected and unexpected market changes. In this context, the complexity of designing agile production networks is a major challenge. This paper proposes the integration of simulation and machine learning (ML) in a single methodology to manage and understand the complexity of designing agile production networks. Accordingly, a brief introduction to the design of agile production networks and related work will be provided. On this basis, the authors explain the integration and functionalities of simulation and ML. The paper provides a ground for further developments and shows further potentials as part of a design methodology utilizing simulation and ML.

Introduction

Agility as a concept has existed in the systems theory of organizations since the 1950s [1]. In recent decades, the term agility has been coined by agile software development. Currently, agility in the context of production networks is seen as the answer to rapid and disruptive change [2]. Consequently, agility and the ability to change have become decisive keys and competitive factors [3].

The challenge of agile production networks is the complexity of their design. In detail, it requires the consideration of all relevant changes in influencing factors and the analysis of effects on the network [2].

Due to the size and interconnectedness of the entire production network, the number and variety of products and the depth of value-added, inadmissible simplifications in the network design are selected by the human preference [4, 5]. As a result, only a few network configurations emerge, which are often inferior to the network variants that could be identified in a more-advanced design process [6]. As a solution, machine learning (ML) can be used to generate network design variants that deviate from human-known patterns [7].

1 Fundamentals

1.1 Design of agile productions networks

A production network is a network consisting of at least two production sites. The production sites are assigned to a single company in terms of their value creation. Supply Chain Networks (SCN), which represent external networks with locations of different companies, can be distinguished from this. Complementary, agility in the context of production networks describes a system that can quickly and economically identify and strategically respond to both expected and unexpected changes in its environment. The design requires the consideration of all relevant changes in influencing factors, the analysis of effects on the network, and derivation and implementation of required actions [1].

1.2 Methods of simulation modelling

A method of simulation modeling describes a general framework for mapping a real-world system to its model. Modeling methods in simulation can be divided into traditional (e.g., discrete event simulation) and less conventional methods (e.g., system dynamics or agent-based modeling) [8, 9]. Discrete event simulation (DES) provides an intermediate level of abstraction and models a process as a s series of discrete events.

DES focuses on operations of individual entities as a system and visualizes them as a process flowchart. System dynamics (SD) operates at a high level of abstraction and is focused on the overall operation of networks rather than on the individual behavior of entities [8]. Agent-based models (ABM) are made up of self-directed agents that follow predefined rules to achieve their objectives whilst interacting with each other and their environment. The system behavior emerges as a summary of the individual actions of agents and is applicable for both low and high level of abstraction [9].

1.3 Machine learning techniques

ML is the ability of computer programs to learn knowledge and strategies through parameter optimization. ML is divided into supervised learning (SL), unsupervised learning (UL), and reinforcement learning (RL), which are distinguished by the nature of the problem and the learning. In SL, a system is trained to produce a specific output given a specific input. UL is used to find patterns in input data without the learning system knowing target values or rewards. RL is used to train and learn a strategy as an agent to maximize a specific reward [10]. The learning agent interacts with an environment that represents the system to be optimized. The agent observes the environment, performs actions in it, and receives rewards or evaluations from the environment for these actions [11].

2 Related Work

In the literature, several approaches have been presented focusing explicitly on the design, evaluation, and optimization of production networks. Available approaches can be structured according to their process-related and analytical complexity into process models, mathematical optimization models, combined approaches (which include a process model and a mathematical optimization model), and approaches in general belonging to the field of multi-attribute decision making [4]. Approaches that explicitly focus on simulation and ML are, therefore, increasingly found in the research field of SCN. The following articles provide insight in the integration of simulation and ML:

- *Aghaie and Heidary (2018)* modeled a multi-period stochastic supply chain with uncertain demand and supplier disruptions. The objective was to determine the best behavior of a risk-sensitive retailer with respect to forward and option contracts during multiple contract periods. .
  For this purpose, an agent-based discrete event simulation approach was developed to simulate the supply chain and its transactions between retailers and unreliable suppliers. As a complement, RL was used to optimize the simulation procedure. A comparison between the numerical results and a genetic algorithm showed the significant efficiency of the proposed RL approach [12].
- *Kemmer et al. (2018)* investigated the performance of RL agents in a supply chain optimization environment. The environment was modeled as a Markov decision process, in which decisions must be made at each step about how many products to produce in a factory and how many products to ship to different warehouses. The results demonstrated that RL agents are able to understand simple market trends, regulate production levels, and efficiently allocate inventory in a simple model scenario [13].
- *Stockheim et al. (2003)* present a decentralized approach to SCM based on RL. The approach consists of loosely coupled yield-optimizing planning agents that attempt to learn an optimal acceptance strategy for sequencing production orders. In a performance comparison, the RL solution was shown to outperform the simple acceptance heuristic [14].

3 Integration into a Design Methodology

The question how simulation and ML can be integrated in a common design methodology has to be answered in three steps. First, it must be determined, how simulation and ML can be integrated in a common use case. Based on this, it must be clarified which modeling method best represents a production network. Third, it must be determined, which specific ML technique can be combined with the selected simulation method to solve the specific challenges of the design case.

The common use of simulation and ML can be implemented as integration of simulation into ML (SIM-assisted ML) or as integration of ML into simulation (ML-assisted SIM). According to the German Engineers Association VDI, Simulation-assisted ML is classified as category D and ML-assisted Simulation as category C of a hierarchical combination [15]. The simulation-assisted ML provides an additional source of information for the ML beyond the usually available data.

Typical functionalities are extending training data, defining parts of the hypothesis approach in terms of empirical functions, driving training algorithms in generative adversarial networks, or testing the final hypothesis for scientific consistency. The ML-assisted simulation is usually used to support the solution process or to detect patterns in simulation data. Typical functionalities are reduction of model order and development of surrogate models that provide approximate but simpler solutions, automatic inference of an intelligent choice of input parameters for a next simulation run, a partially trainable solver for different equations, or identification of patterns in simulation results for scientific discovery [16].

The selection of a modeling method is conducted by analyzing real-world examples and specific case studies. In this context, the selection of a suitable abstraction level for the model and the identification of entities involved as well as their properties and relationships is crucial [17]. Production networks have similar properties like SCNs [2]. However, SC entities operate with different constraints and objectives. Each decision made by any entity impacts other partners. Thus, improving the performance depends on all entities' willingness to collaborate and their ability to coordinate their activities. For this reason, SCNs and production networks can also be defined as a complex adaptive system (CAS). A CAS is a dynamic network where many agents simultaneously and continuously react to the actions of other agents [18]. An approach to model CAS is ABM, describing systems as being made up of self-directed agents. These follow rules to achieve their objectives whilst interacting among each other and with their environment. This allows for investigating the emergent behavior of a system [19].

In addition, an appropriate ML technique must be selected for the use in a design methodology. For this selection, the specific challenges of the design case provide useful indications. In the case of agile production networks, these include the lack of transparency about external and internal influencing factors, an undifferentiated assessment of their effect on the factory, low validity and traceability of the selection of situation-specific measures to increase agility, and the complex estimation of costs and benefits associated with agility measures. Consequently, there is a lack of a decision-making basis to take measures that make a network adaptable for the specific-situation [2]. A ML technique for this kind of decision-making problems is RL.

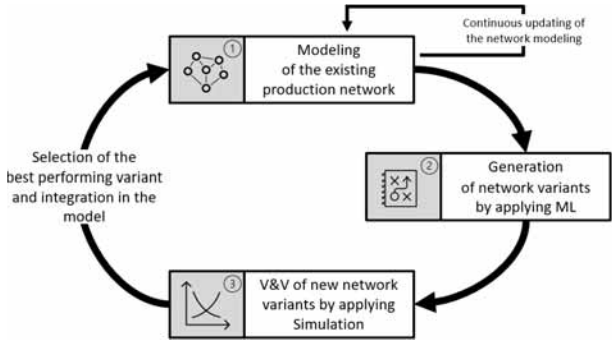

Figure 1: The design methodology is a cycle consisting of three phases.

For RL, an implicit part of the observation is whether the outcome state is good or bad relative to the agent's performance metric. On these observations, the agents can generate optimal plans that determine the proper action to take in any state [11].

Based on the proven applicability of RL and ABM in the application field of production networks, a superordinate process model for a design methodology is visualized in Figure 1 and presented below.

The starting point (Phase 1) of the design methodology is the modeling of the existing production network. In this phase, due to changes in the market and within the company, changes in the production network must be continually monitored and included in the modelling state. In Phase 2, the generation of network variants with suitable technical models (e.g., ML technqiues) is required. Here it is necessary to cover the characteristics of agility enabler in production network [20]. Finally, a validation and verification (V&V) of the network variants is carried out by applying simulation. A suitable V&V support the process of model creation, as well as the use of the model and the evaluation of the simulation results [21]. As solution objective, the most performing network variant is selected and integrated into the network modeling as the current state of the production network.

4 Conclusion and Outlook

This short paper presents how simulation and machine learning (ML) can be used and integrated in a common design methodology. By combining agent-based models (ABM) with Reinforcement Learning (RL), an approach to manage and understand the complexity in the designing of agile production networks could be identified.

With ABM, interactions in the production network can be investigated, the system behavior can be understood and the entire complexity of a production network can be captured. Consequently, it is possible to understand how individual network adjustments can affect the entire production network. Based on this, RL algorithms are used to train the ABM agents for network design variants that are more independent of human preferences. Through the RL training, the entire design process including all possible network variants is captured. As a result, the agents can create resilient and optimal design decisions that determine the correct action in each state of the production network. For further research, it remains to be investigated which specific level of modeling abstraction is sufficient for production networks. In addition, other modeling methods such as Petri Nets should be investigated. Finally, it must be determined which integration form of simulation and ML provides more advantages for the use case and which potential target values should be trained with RL.

References

[1] Brock D, Junge M, Krähnke U. Soziologische Theorien von Auguste Comte und Talcott Parsons. Oldenbourg Verlag, Munich Germany 3rd ed. (2012).

[2] Ays J. Gestaltung agiler Produktionsnetzwerke. Apprimus, Aachen Germany (2021).

[3] Löffler C. Systematik der strategischen Strukturplanung für eine wandlungsfähige und vernetzte Produktion der variantenreichen Serienfertigung. Jost-Jetter Verlag, Stuttgart Germany (2011).

[4] Auberger E, Karre H, Wolf M, Preising H, Ramsauer C. Configuration of manufacturing networks by a multi-objective perspective enabled by simulation and machine learning. 54th Conference on Manufacturing Systems, 104, 993–998 (2021).

[5] Wiezorrek A. Beitrag zur Konfiguration von globalen Wertschöpfungsnetzwerken. Ph.D. Thesis, TU Dortmund, Chair of Enterprise Logistics, Dortmund Germany (2017).

[6] Sage B. Konfiguration globaler Produktionsnetzwerke. Herbert Utz, Munich Germany (2018).

[7] Krueger J, Fleischer J, Franke J, Groche P. KI in der Produktion: Künstliche Intelligenz erschließen für Unternehmen. WGP Wissenschaftliche Gesellschaft für Produktionstechnik, Berlin Germany (2019).

[8] Law AM. Simulation Modeling and Analysis. McGraw-Hill Education, New York USA 6th ed. (2024).

[9] North MJ, Macal CM. Introductory tutorial: Agent-based modeling and simulation. Proc. of the Winter Simulation Conference, IEEE, Piscatawy NJ, 1456–1469 (2011).

[10] Waschneck B. Autonome Entscheidungsfindung in der Produktionssteuerung komplexer Werkstattfertigungen. Fraunhofer Verlag, Stuttgart Germany (2020).

[11] Liu Y, Yang M, Guo Z. Reinforcement learning based optimal decision making towards product lifecycle sustainability. International Journal of Computer Integrated Manufacturing, 35, 1269–1296 (2022).

[12] Aghaie A, Hajian Heidary M. Simulation-based optimization of a stochastic supply chain considering supplier disruption: Agent-based modeling and Reinforcement Learning. Scientia Iranica, 26 (6), 3780–3795 (2018).

[13] Kemmer L, von Kleist H, de Rochebouet D, Tziortziotis N, Read J. Reinforcement Learning for supply chain optimization. In: 14th European Workshop on Reinforcement Learning, Lille France, 1st–3rd October (2018).

[14] Stockheim T, Schwind M, Koenig W. A Reinforcement Learning approach for Supply Chain Management. 1st European Workshop on Multi-Agent Systems, Oxford UK, 18th–19th December (2003).

[15] Association of German Engineers. VDI 3633, Part 12, Simulation of systems in materials handling, logistics and production. Beuth, Berlin Germany (2020).

[16] Von Rueden L, Mayer S, Sifa R, Bauckhage C, Garcke J. Combining Machine Learning and simulation to a hybrid modelling approach: Current and future directions. In: Berthold, M.R., Feelders, A., Krempl. G. (eds.): Advances in Intelligent Data Analysis XVIII, 548–560. Springer, Cham Switzerland (2020).

[17] Keramydas C, Dimitrios B, Dimitrios A. Agent-based simulation for modeling supply chains: A comparative case study. International Journal of New Technology and Research, 2, 36–39 (2016).

[18] Dominguez R, Canella S. Insights on multi-agent systems applications for supply chain management. Sustainability, 12 (5), article 1935 (2020).

[19] Sadat Hosseini Khajouei MH, Pilevari N, Radfar R, Mohtashami A. Complex adaptive systems, agent-based modeling and supply chain network management: A systematic literature review. Journal of Industrial Engineering and Management Studies, 8, 54–92 (2021).

[20] Erlach K, Berchtold M, Kaucher C, Ungern-Sternber, R. Gestaltung resilienter Produktionsnetzwerke mit Agilitätsbefähigern: Standortrollen als Lösungsansatz in der Fabrikplanung. Zeitschrift für wirtschaftlichen Fabrikbetrieb, 118, 4, 217–221 (2023).

[21] Rabe M, Spiekermann S, Wenzel S. Verifikation und Validierung für die Simulation in der Produktion und Logistik. Springer, Berlin Germany (2008).