Challenges for Achieving Supply Chain Resilience and Transparency within CoyPu

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Abstract

Supply chain resilience and transparency are important for the ability of companies to react flexibly to the changing conditions of the environment and the market, especially in crisis situations. Events such as pandemics or economic crises can lead to sharp changes in demand or a halt in production as well as bottlenecks along supply chains. In the project CoyPu, which tackles the complex economic challenges in crisis situations by integrating heterogeneous data and solutions into an intelligent platform, we put particular focus on the two use cases demand forecasting and resilient production. An accurate demand forecast is important for companies to accurately plan production. This need is amplified in supply chains containing semiconductors, since long production times limit flexibility. Especially in times of disruptions tactical demand forecasts and the Bullwhip Effect, which amplifies demand along the supply chains, further complicate demand forecasting. This requires alternative demand forecasting approaches to tackle the before-mentioned issues. To meet the forecasted demand, smooth production processes are necessary, which rely on parameters such as precise predictions of material availability to optimize the production start time. Due to intransparent supply chains, which lack information such as subsuppliers or specific source locations, it is challenging to obtain accurate predictions and find the best alternative solution in case of adverse events. To address these issues on both the demand and supply side, CoyPu aims at enabling high-quality and insights into economic trends and forecasts, based on cognitive modeling of data within a system of networked knowledge graphs and configurable artificial intelligence analysis tools. This paper highlights major challenges on the demand and supply side and possible solutions to achieve an optimized demand forecasting and a more resilient production.

Keywords

Supply chain, crisis prediction, knowledge graphs, artificial intelligence, demand forecasting, resilient production

1. Introduction

Resilience and planning security of complex global supply chains and production are generally important but especially in crisis situations in order to be able to react flexibly and agilely to the

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changing conditions of the environment and the market. Crisis situations such as pandemics or economic crises can lead to sharp changes in demand or a halt in production as well as bottlenecks along supply chains.

The CoyPu project addresses the complex economic challenges in crisis situations with an intelligent platform for integrating, structuring, analyzing, and evaluating heterogeneous data from economic value networks as well as the industry environment and social context. Based on cognitive modeling of data within a promoted system of networked knowledge graphs and flexibly configurable AI analysis tools, the CoyPu platform enables high-quality and insights into economic facts, trends, impact relationships, and forecasts. The crisis-relevant questions that can be answered in this way can concern individual value networks or concrete value chains, focus on different regions, industries or company sizes, or be located at the overall economic level. To avoid supply bottlenecks, it is therefore necessary to identify production-, system- and crisis-relevant goods and their supply routes in advance. The project develops the technical prerequisites for the preventive analysis of crisis and disaster situations and thus enables decisions to increase the resilience of supply networks.

Two complementary perspectives are used as a basis for the development of the solution. On the one hand, (a) company-level resilience and crisis effects are focused on for concrete value chains, and on the other hand, (b) cross-value-chain effects on the level of markets, industry ecosystems, regions, or the overall economy are considered. This paper highlights the challenges and possible solutions by working on the perspective (a). The two use cases, which will be described in more detail in the following, are:

- Optimization of demand forecasting: increasing planning flexibility and reliability.
- Resilient production: risk identification and mitigation with regard to critical parameters, e. g., production and storage sites, production processes, and supply chains.

2. Use Cases Overview

In order to achieve resilience in the face of disruptions and events, CoyPu will facilitate a knowledge graph-based approach that aims to optimize demand forecasting as well as production. Siemens leads the use case about resilient production, focusing on the supplier side and disruptions impacting relevant materials. On the demand side, Infineon aims to improve existing demand forecasting by connecting relevant external data concerning demand drivers. Both use cases will use ontologies as the basis to model supply chains as well as events and trends and integrate data into knowledge graphs to achieve the use case goals. However, challenges regarding the Bullwhip Effect or supply chain transparency complicate the use cases substantially. The following sections introduce the demand forecasting and resilient production use case. Each use case outlines major challenges, highlights background information, and proposes potential solutions.

3. Optimization of Demand Forecasting

Infineon's use case concerns optimized demand forecasting. There are unique challenges on the demand side need to be targeted in the case of the semiconductor industry. Due to the high level of sophistication and complexity that is inherent to semiconductor devices, production is time consuming and costly. Processes include thousands of steps, which, due to the high levels of precision required by the miniature scale of the product as well as its layered architecture, have to be performed in sequence and often repeated multiple times [1]. This leads to production cycles routinely exceeding four to six months [2]. High costs of both operating and expanding manufacturing facilities, due to the requirements for equipment and manufacturing environments, pose additional challenges. Constructing a new facility involves high costs and sites have to operate in 24/7, year-round production in order to remain profitable, with facilities constantly running near or at maximum capacity [3]. Forecasting is therefore essential to the industry, as ramping up production or increasing capacity on short notice is challenging faced with the mentioned characteristics of the industry. Challenges arise here in the domain of forecast accuracy, which depends on receiving representative demand pictures from customers for better planning of production. In addition to the before-mentioned industry characteristics, tactical demands in forecasting and ordering as well as the Bullwhip Effect as major challenges need to be taken into account for the use case.

3.1. Tactical Demand

One of the greater challenges in the domain of demand forecasting stems from the communication of tactical demand numbers by customers. Instead of the true demand, companies tend to report inflated, tactical demand data to ensure that their orders will be fulfilled. This leads to a less optimal production planning and constitutes a significant problem particularly in times of disruptions. This behavior is incentivized by the way how ordering systems in times of scarcity are set up. When inventories are low, products will be distributed through allocation, which is done via manually assisted distribution to customers. Typically, only a certain percentage of any given order can be fulfilled in this scenario. Thus, communicating a number that exceeds the originally required amount two- or three fold ensures that orders will be fulfilled completely [4]. Psychological effects and resulting behavioral order mechanisms related to the anticipation of scarcity are further contributors to inflated orders. When faced with the possibility of an emerging shortage, buyers tend to respond in a way that fixates on loss aversion while prioritizing risk aversion second and possible gains last. They will often exhibit probability weighing behavior, in which the likelihood of a shortage is misinterpreted and often overestimated. This correlates closely with the concept of prospect theory, which suggests that risk will typically be sought out to avoid losses when faced with a risky decision where they seem likely, while risk will conversely be avoided when gains appear more probable [5]. Research suggests that as a result, orders may come within the range of up to 2500% of baseline demand when customers anticipate a shortage [6]. These inflated demand numbers further complicates demand forecasting and subsequently production planning.

3.2. Bullwhip Effect

Another major challenge affecting demand forecasting is the Bullwhip Effect. Companies that are situated in the upper echelons of a supply chain and therefore separated from end customers by multiple levels are impacted substantially by demand miscommunications since

Figure 1: The Bullwhip Effect mirrored in semiconductor market growth vs. global real GDP, 2005-2021. Smoothing can be observed in the 2020 shortage over 2008-2010, but there is still room for improvement [8].

the demand signal is amplified by the Bullwhip Effect. This is a well-known phenomenon, in which demand signals become distorted as they travel up a supply chain. As the signal progresses upstream, it intensifies at every stage to the point where the demand picture received in the upper echelons no longer reflects reality [7]. The Bullwhip effect, as seen in figure 1, has been observed extensively and has again played a major role in the (as of the writing of this paper) ongoing global chip shortage. Demand miscommunication constitutes a key contributing factor for the development and facilitation of the Bullwhip Effect in semiconductor supply chains and coincides with additional challenges. These consist mainly of characteristics of the semiconductor industry conflicting with operational practices throughout other supply chain levels. In the automotive industry in particular, it is commonplace to rely on methods such as just-in-time, the pull principle, or reach steering for inventory management [9]. These practices may work well within the lower tiers of the supply chain but can create issues upstream, as they lead to deviations from forecasts that may not be able to be fulfilled given the aforementioned limited flexibility of semiconductor manufacturing based on the industry characteristics. This leads to additional demand uncertainty, which culminates in an inaccurate demand picture and facilitation of the Bullwhip Effect. With respect to machine learning, this poses further issues, as demand data subsequently includes bias of the tactical demands and noise which is amplified by the Bullwhip Effect. Any machine learning model trained on those data sets will therefore learn the same bias and noise patterns and will be inaccurate at demand prediction in the face of cancelled orders. As a result, companies may produce the wrong products at the wrong volumes and are confronted with high inventory costs.

3.3. Solution Approach

To improve forecast accuracy in the context of semiconductor manufacturing, a referencing system of customer demand with other data could present an opportunity to circumvent some of the challenges posed by information asymmetries. External information like market or customer

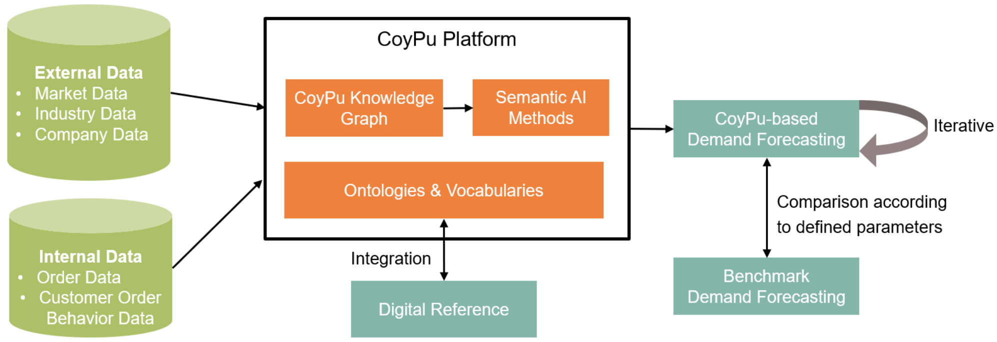

Figure 2: CoyPu optimization of demand forecasting approach.

circumstances can be independent of tactical demand information and amplifications by the Bullwhip Effect and act as a valuable indicator for future demand. Therefore, in addition to order and forecast information, the demand forecasting use case includes independent external and internal context information to improve forecasting performance.

This is addressed by the architecture seen in Figure 2 within CoyPu. External data augments demand forecasts that are solely based on customer forecasts, which includes organization, market and industry information. Additional internal information serves as further context information in the forecasting. Both, external and internal data sources are the input for the demand forecasting system. Subsequently, data is prepared and transformed for the generation of a CoyPu knowledge graph. The added value of such an approach stems from a viewpoint that integrates and connects data in networks rather than including data silos. A graph structure allows to capture the highly connected internal and external data sources. Ontologies provide the semantic basis for the semantic data integration and a common vocabulary. These include existing models like the Digital Reference [10], a supply chain ontology for semiconductor supply chains as well as generic supply chains. The ontology enables humans to understand the domain of forecast-relevant information as well as relationships between products, customers, and demand drivers. At the same time, the resulting knowledge graph is usable by machines and can be used for visualizations, analytics, and the CoyPu-based demand forecasting. Using semantic artificial intelligence methods, a data-driven demand forecast will be implemented and iteratively compared to benchmark demand forecasting methods to evaluate the results. With the knowledge graph-based approach, an increased transparency along supply chains can be achieved. Furthermore the parallel stream is independent of tactical demands and the Bullwhip Effect. By including trends and events from various sources, the overall goal of better understandability and prediction of demand is enabled.

4. Resilient Production

Production processes depend on numerous global aspects, such as multiple production locations, multiple parts storages, and global provider networks. A well-established and complex supply network might be disturbed or even broken by unpredictable events. Examples of such events are pandemics, embargos, environmental disasters, military conflicts, and economic crises. Any of these events may cause local production bottlenecks or even production stops, which will affect all subsequent processes. Schroeder et al. [11] studied the effects of the Covid-19 pandemic on manufacturing and trading companies and found that 64% of these companies experienced negative effects in the procurement area while supply chain risk management was often only available on a small scale or even not available at all. Especially companies that rely on just-in-time production depending on one single supplier face enormous challenges if the supply chain is disrupted [12].

Within CoyPu, Siemens works on resilient production with the goal to identify risks with regard to critical parameters in, e. g., supply chains and production processes, and to demonstrate how early risk evaluations could enable counter measures and therefore enhance production resilience.

4.1. Supply Chain Transparency

In a supply chain network, each participant has only limited information in each direction. While companies usually know their direct (tier-1) customers and suppliers, almost 80% of the companies cannot name the number of their subsuppliers (tier-2 or tier-n suppliers) [13]. Going further in each direction continuously decreases the transparency, also due to the unwillingness of companies to share data with their suppliers and customers, which could be considered a competitive disadvantage and result in a negative impact for the own business. Furthermore, supply chain data generally suffer from incompleteness, e.g., source locations of materials cannot be easily derived from sales office locations. Starting with the direct suppliers, tracking preceding steps within the supply chain, even back to raw material production, would be helpful to get a more reliable picture of the risks, critical paths, and bottlenecks in the supply network. Transportation routes of product parts as well as stock supply in material warehouses should be considered as well and integrated in the risk management process.

Decisions in supply chain risk management are made based on internal data, estimations about uncertain information in the supply chain, and publicly available knowledge. In a survey, at least 75% of the companies see need for improvement considering the transparency in the supply chain and methods for risk identification [13]. Creating more transparency in the supply chain is an active research topic [14], where successful implementations can lead to better informed decision making processes, more flexible risk mitigation strategies, and more resilience in the production.

4.2. Production Start Time Optimization

Risks in the supply and value chain at the level of the individual productions mostly have an effect on time. The risk either affects the starting times of production orders, the order sequence in the production schedule, or even the production duration. In other words, to make production more resilient, there is a need for more transparency, including information-based management of operators on the shop floor, in order to make optimal operational decisions and thus mitigate the impact of any adverse events.

One way to increase the value and quality of information on the shop floor is through

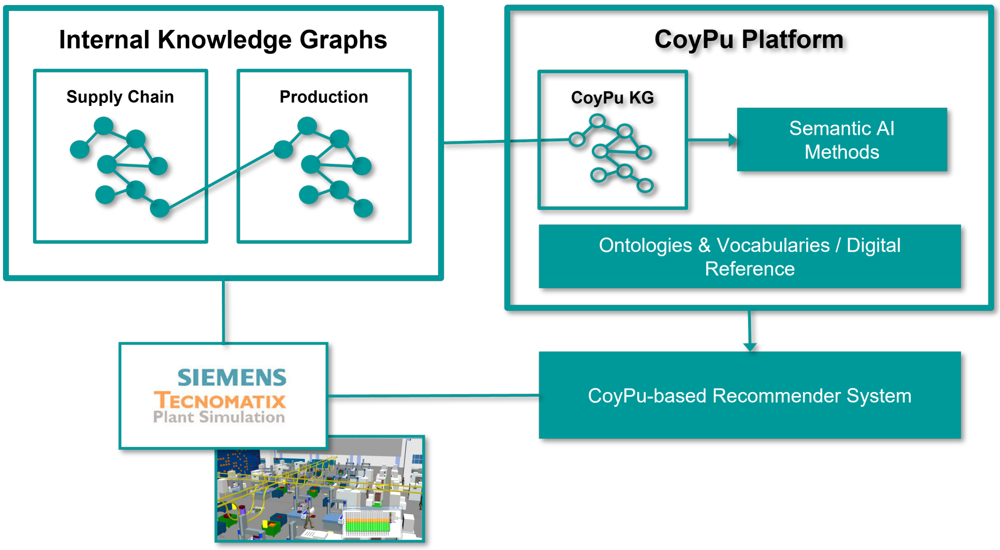

Figure 3: Resilient production use case in CoyPu.

simulation. Correlating the current situation of production (i. e., orders, resources, and stocks) with the influencing factors in a production-related simulation model builds a powerful basis for decision-making, which operators can continuously use in their daily tasks. With this information, the operators can take an informed decision when to start which order to remain efficient despite the turbulences in the supply and value chain.

The basis of the start time point optimization lies in the interconnection of the simulation of the distribution logistics and the material flow simulation of the production. This comprehensive model creates the possibility to grasp the effects of unforeseeable events early and to analyze them on the basis of the production simulation. One possible scenario is ensuring material availability for a specific production order. In particular, if the material is not available at the start time, but a delivery is planned. Here, a simulated confirmation with a certain probability score becomes the condition to start the order in advance.

4.3. Solution Approach

Precise material availability predictions are essential for a smooth production process. Reliable identification and assessment of related supply chain risks are fundamental to allow for risk management in a timely manner. To better understand the production processes, existing or planned production plants can be modeled as virtual twins, which are used to simulate the material flow in the plant to determine when a certain material needs to be available to complete the production on time.

Risks like delayed transport or disruptive events can directly influence production results and production site utilization. The identification and evaluation of these risks are based on internal and external data, including information about suppliers, products, and logistics. The data is prepared and transformed into a knowledge graph, where the knowledge graph from

CoyPu extends the data available from internal knowledge graphs. The ontology developed within CoyPu as well as existing ontologies, such as the Digital Reference [10], serve as the basis for the knowledge graph modeling. Machine learning methods and graph analysis techniques are used to derive risks and knowledge from the data, e.g., critical paths and bottlenecks in the supply chain, relevant crisis events, or properties of a delivery. Further, the results can be annotated with scores, which could be interpreted as risk or probability scores, to facilitate the understanding of the results. The outputs of the artificial intelligence algorithms are part of a CoyPu-based recommender system (see Figure 3), which acts as a decision support tool for the domain expert. Based on the recommendations, the experts in the logistics or procurement department can decide on the proper mitigation measures.

5. General Challenges

The previous sections focused on specific demand and supply challenges in the use cases as well as solution approaches. In this section, further general challenges are highlighted, which also need to be taken into consideration during the development of the use cases.

- **Domain inherent complexity:** A further challenge is that cause-effect relationships are difficult to measure. Explaining the consequences of an event when it has not happened yet is hard to forecast. Both production processes and supply chain processes are complex and can have many variations at any time scale. Positive and negative effects on demand or supply can cancel or amplify each other, adding another dimension of complexity.
- **Complexity of data model and volume of data:** Modeling supply chain and production processes in a knowledge graph requires domain experts for meaningful results. Furthermore, data scientists have requirements on modeling because machine learning algorithms might require specific input structures. For machine learning, data complexity might create a performance problem. This challenge might need abstraction of complexity at an early stage of modeling and scalability of technologies and hardware.
- **Heterogeneity and rarity of crisis:** Crisis and disruptive events are rare and considerably heterogeneous. The data from different crises, for instance, the financial crisis of 2010 or the pandemic of 2020 cannot be compared since their causes and effects are largely different. Therefore, past crises can serve as benchmarks but will not be enough to train data-driven AI approaches.
- **Data security and quality:** The aspect of considering information security should be common practice. Beyond this, the aspect of data quality, i. e., incomplete, incorrect, inaccurate, or out-of-date data must also be considered. All these aspects might derive from both data complexity and data volume. Data ingestion and machine learning must handle all of this to be reliable.
- **Dependency between data models and machine learning methods:** The applied machine learning methods and available data need to be compatible with each other to effectively solve the problems posed within the use case. The correct definition of the data model can greatly influence the performance and usability of the algorithm. Different kinds of machine learning approaches also have different requirements concerning the data, e. g., supervised learning relies on labeled data for predictions, while unsupervised

learning discovers patterns in unlabeled data. The data model as well as the machine learning algorithm usually need to be developed and adapted in an iterative manner.

- **Explainability of machine learning results:** Existing machine learning models, in particular subsymbolic methods, often lack explainability and transparency, i. e., it is not clear what exactly contributed to specific predictions or scores. Non-domain experts might have difficulties understanding the predictions, but even domain experts who are familiar with supply chain management and production might be hesitant to apply black-box methods if they cannot trust them. Symbolic methods usually offer better explainability, e. g., in the form of rules, but often suffer from scalability issues. Explainability, however, is crucial for a wider adoption of machine learning methods in industry.
- **Trusted visual analytics:** Decision makers will need comprehensible user interfaces to take proper actions. Even if machine learning results may be comprehensible to data scientists, an intelligent user interface for explaining results, data, and models is required for the model to be trustworthy and understandable to decision makers. It must also allow us to make ethical, correct, and unbiased decisions. Frequently, this could be a decision between compliant and economical actions.
- **Combine simulation of risk events with plant simulation:** With reinforcement learning, it would be possible to train an agent to react suitably to certain events or disruptions. This would require simulating such events in combination with a simulation of the production plant. However, this will become extremely complicated since it would basically mean to simulate realistic supply chain events (e. g., material shortages and delays), create artificial bills-of-processes, bills-of-materials, and then define and simulate key performance indicators for the factory.

6. Conclusion and Future Work

Our work identified and presented challenges on the road to achieving supply chain resilience and transparency within the CoyPu project's industry use cases. Some of these challenges can be addressed by the application of semantic technologies. The inherent complexity of the domain can be mitigated by using ontologies to structure the domain and capture knowledge and complex relations found in data. Furthermore, knowledge graphs are known to handle heterogeneous data from different data silos well and provide the basis for an intuitive visualization for analytics with dashboards. They also allow for an extensible data structure to handle and connect extensive amounts of data from various sources.

Solving the issues with tactical demand and the Bullwhip Effect can be enabled by relying on external indicators for demand forecasting or collaborative demand forecasting approaches such as anonymous surveys. Furthermore, a lack of transparency in supply chains can be improved by connecting external with internal data, making use of publicly available information. The combination of risk identification with plant simulation requires a common framework, which needs to be developed with the corresponding partners.

Further next steps in the mitigation of the above-mentioned challenges in the CoyPu project are the creation of further domain models, such as a supply chain ontology. These should be able to handle heterogeneous data from the industry. The knowledge graphs are the result of the data mapping and will be used by demonstrators for demand forecasting and resilient production including dashboards for visualization.

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References

[1] T. Ponsignon, Modeling and Solving Master Planning Problems in Semiconductor Manufacturing, Ph.D. thesis, 2012.

[2] O. Burkacky, S. Lingemann, K. Pototzky, Coping with the auto-semiconductor shortage: strategies for success, 2021. URL: https://www.mckinsey.com/industries/automotive-and-assembly/our-insights/coping-with-the-auto-semiconductor-shortage-strategies-for-success.

[3] H. Ehm, T. Ponsignon, T. Dr. Kaufmann, The global supply chain is our new fab: Integration and automation challenges, 2011, pp. 1–6. doi:10.1109/ASMC.2011.5898164.

[4] H. Lee, V. Padmanabhan, S. Whang, Information distortion in a supply chain: The bullwhip effect, Management Science 43 (2004) 546–558. doi:10.1287/mnsc.1040.0266.

[5] J. Foster, C. Deck, A. Farmer, Behavioral demand effects when buyers anticipate inventory shortages, European Journal of Operational Research 276 (2019) 217–234. URL: https://ideas.repec.org/a/eee/ejores/v276y2019i1p217-234.html. doi:10.1016/j.ejor.2019.01.00.

[6] J. Sterman, G. Dogan, "i'm not hoarding, i'm just stocking up before the hoarders get here.", Journal of Operations Management 39-40 (2015). doi:10.1016/j.jom.2015.07.002.

[7] A. Beer, Der Bullwhip-Effekt in einem komplexen Produktionsnetzwerk, Springer Fachmedien Wiesbaden, 2014. URL: https://doi.org/10.1007/978-3-658-06118-0. doi:10.1007/978-3-658-06118-0.

[8] A. Ismail, H. Ehm, Mitigating the bullwhip effect in the end-to-end semiconductor supply chains using end-to-end supply chain simulation, 20, IEEE, 2021.

[9] F. Klug, Beschaffungslogistik im Automobilbau, 2018, pp. 329–403. doi:10.1007/978-3-662-55873-7_8.

[10] Digital Reference, Digital reference, 2022. Https://w3id.org/ecsel-dr.

[11] M. Schroeder, B. von See, J. Schnelle, W. Kersten, Impact of the Covid-19 Pandemic on Supply Chain Management, Springer Fachmedien Wiesbaden, Wiesbaden, 2021, pp. 3–24. doi:10.1007/978-3-658-33480-2_1.

[12] I. Raehlmann, Corona! Die Krise der Verschlankung und ihre Folgen, Zeitschrift für Arbeitswissenschaft 74 (2020) 216–221. doi:10.1007/s41449-020-00216-9.

[13] M. Brylowski, M. Schröder, W. Kersten, Machine learning im supply chain risk management: Studie, 2021. doi:10.15480/882.3875.

[14] M. Montecchi, K. Plangger, D. C. West, Supply chain transparency: A bibliometric review and research agenda, International Journal of Production Economics 238 (2021). doi:10.1016/j.ijpe.2021.108152.