6th Conference on Production Systems and Logistics

Early Warning System To Increase Supply Chain Resilience

Theresa-Franziska Hinrichsen[1], Eduardo Colangelo[1], Adrian Wrobel[1]
[1] *Fraunhofer Institute for Manufacturing Engineering and Automation IPA, Stuttgart, Germany*

Abstract

Various crises in recent years, such as the COVID-19 pandemic and the Ukraine war, have exposed the vulnerability of global supply chains. In the resulting strive to become more resilient, enterprises have realized that existing supply chain risk management (SCRM) systems are insufficient. The current practice of enterprises can be described as "firefighting", as interruptions are often recognized only after they become evident and, consequently, measures are taken reactively. In order to be able to detect deviations from the planned state in an early stage and to take measures preventively this paper proposes creating a proper early warning system (EWS). This would function by monitoring changes on the procurement market, focusing on supply shortages and price shifts. For this purpose, easy to acquire data is observed, such as indices or market prices for raw materials. This paper begins by analysing the requirements for a resilient supply chain and an EWS. A review of existing systems and methods forms the basis for the state of the art. This is followed by the identification and evaluation of influencing factors and the analysis of corresponding indices. The proposed approach is then described, concluding the paper with a validation of the concept.

Keywords

Early Warning Systems; Resilience; Supply Chain; Crisis Management

1. Introduction

1.1 Resilience in the context of supply chain

In recent years and decades, the primary aim of many companies has been to configure efficient and cost-effective supply chains: global sourcing and low stocks combined with low fixed costs and high profit were measures in order to succeed in tough price competitions [1]. Especially, the expansion of globalization has led to an increase in the complexity of supply chains. This, together with the dynamics within the global economy, poses a growing challenge for companies in the event of a disruption. Companies need more time to adapt but, simultaneously, they have less time to react [2], as shown in Figure 1.

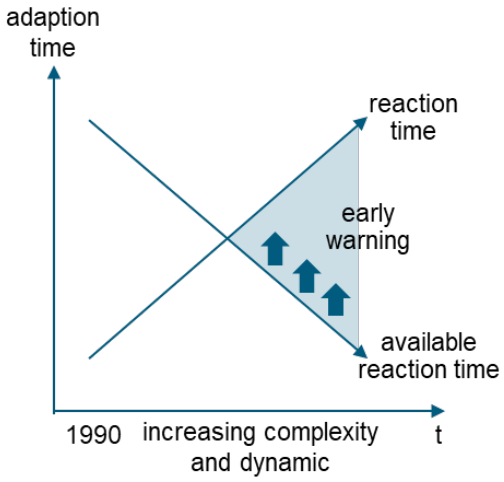


Figure 1: Correlation between adaption time and increasing complexity and dynamic [2]

Shortages of raw material in the last four years highlighted such vulnerability of supply chains. The most important weak points are uncertainty, risk factors and the resulting disruptions and interruptions. Figure 2 shows the connection between these aspects. *Uncertainty* is characterized by the incompleteness of knowledge about the system and its environment. The term *risk* is defined in different

DOI: https://doi.org/10.15488/17746
ISSN: 2701-6277

forms in the literature. In the context of this paper, the definition from the discipline of decision theory is used. According to this, *risk* is defined as a measure of the set of possible outcomes of a single rational decision and their probability values. A *disruption* is defined as an unexpected event that interrupts the normal flow of goods in a supply chain network and has a significant negative impact on the operation and performance of the supply chain. Finally, an *interruption* is the result of a disruptions [3].

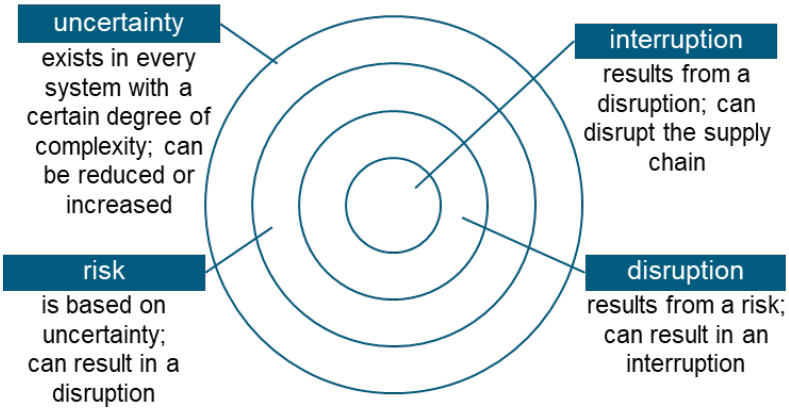


Figure 2: Correlation between influences and impacts on the supply chain, based on [3]

Supply chains require resilience in order to absorb these uncertainties. In the literature, there is no standard definition of the term *resilience*. In the context of supply chain, resilience means adapting quickly in order to maintain the ability to act and, if necessary, to fundamentally redesign structures and processes. Resilience can be divided into five phases: prepare, prevent, protect, respond, recover (see also [4]). The *prepare* and *prevent phase* are essential in order to be informed of disruptions in an early stage. Based on the Supply Chain Operations Reference Model (SCOR), three areas need to be considered: source, make, deliver. On the source side, the focus is on determining replenishment time and price changes. In order to identify production deviations, the focus must be on monitoring incoming orders and observing lead time deviations. From a delivery perspective, the main aspects are the identification of delivery time deviations, e.g. by considering delivery date performance, as well as the predictive determination of such deviations, e.g. by analyzing interruptions. Existing approaches are often very expensive, as they tend work with inaccessible datasets, which makes it particularly difficult for small companies to use them to increase the resilience of their supply chain. In addition, existing early warning systems (EWS) do not provide a systematic approach to considering the different supply chain elements and provide warnings only when a disruption has already occurred. Today, early identification of disruptions requires a lot of expert knowledge and a significant time investment to create a data basis by combining different systems. To close this gap, this paper proposes an approach for an EWS that uses open access data to detect potential disruptions in the supply chain at an early stage. This is based on a systematic approach for determining the optimal warning point and warning limits. The focus is on uncertainties and risks on the procurement side [4].

To describe to proposed approach, chapter 1 begins with a closer look at relevant definitions and procurement risks in order to identify the requirements on an EWS from a resilience perspective. Chapter 2 addresses the requirements and provides an analysis of the state of the art of EWSs. The design of the proposed EWS is then described in Chapter 3. The relevant influencing factors are analyzed and selected before the chosen method is presented. Towards the end of the chapter, a validation of the proposed approach is described. The paper concludes with a summary and an outlook of further research steps.

1.2 Risks in the supply chain

Disruptions in the supply chain are caused by risks. It is therefore necessary to identify them in order to be able to monitor their development. To classify them, various options can be found in the literature (see [5–7]). From a procurement perspective, it is appropriate to differentiate between risks that occur inside and

outside the supply chain. *Inside the supply chain*, risks from the category of supplier risks are relevant. These includes e.g. an increase in procurement costs or the collapse of a supplier. Risks categories from *outside of the supply chain* are environmental and organizational risks. *Environmental risks* includes e.g. political instability or market risks. *Organizational risks* includes e.g. administrative obstacles such as trade restrictions [7]. The complete reduction of risks and elimination of disruptions is not possible. However, using an EWS to warn of potential disruptions can increase the response time and minimize the interruptions.

2. Early warning system

2.1 General view

EWSs are information systems they provide latent signals, symbols or information to their users [8]. The aim is to increase the response time by providing information at an early stage [9, 10]. This is realized by monitoring self-defined indicators, depending on the use case [8]. A distinction can be made between internal-oriented and external-oriented EWSs. While *internal-oriented* EWSs consider the opportunities and risks of the user, *external-oriented* EWSs take into account the uncertainties and risks of market participants. Internal-oriented EWSs (on which this paper focuses) have been continuously developed in recent years and are currently in their fourth generation [11]. The development is shown in Table 1, where also the characteristics are described in more detail.

Table 1: Development stages and characteristics of internal-oriented EWSs

Generation	Characteristics
1. Generation (1973-1977)	**Data type:** quantitative; internal **Approach:** target/actual comparison **Time horizon:** short term
2. Generation (1977-1979)	**Data type:** quantitative and qualitative, internal and external **Approach:** indicator-based systems **Time horizon:** middle term
3. Generation (since 1979)	**Data type:** quantitative and qualitative, internal and external, weak signals **Approach:** based on Ansoff's concept of weak signals (poorly defined and fuzzy structured information) **Time horizon:** long term
4. Generation	**Data type:** quantitative and qualitative **Approach:** network thinking based systems, integrating the first three approaches **Time horizon:** short, middle, long term

Regarding to the time horizon, a distinction must be made between strategic and operational systems, whereby a clear separation is difficult. The clearest distinguishing element is the time horizon. An *operational system* covers a period of up to two years and *strategic systems* 2 to 5 years [11]. In addition, a distinction can be made based on the focus of observation. Operational systems are more crisis-oriented than opportunity-oriented [11]. Because of this, the focus of this paper is on an operational-oriented approach.

Operational EWSs can be divided into three types: key performance-oriented, extrapolation-oriented and indicator-oriented. *Key performance-oriented* EWSs are based on key performance indicator systems, utilize a comparison between target and actual value, and are quantitative and past oriented. *Extrapolation-oriented systems* are based on a comparison between the target values at the end of a period and the extrapolated actual values, which means that feedback information is supplemented by feedforward information. *Indicator-oriented systems* are based on latent events that are not directly observable. In contrast to key performance-oriented systems, attributes are not displayed directly. Indicators can be both quantitative and qualitative [11]. The approach presented in this work is based on this type.

The required characteristics of the proposed system can be derived from the requirements for the selection of indicators. These must be able to depict disruptions, be unambiguous and fully capture all opportunities and risks. Further requirements are timeliness and timely availability. Risks must be able to be identified at an early stage to increase reaction time, and the delay between the collection and provision of the data should

be minimal. In addition, the costs for the system and the data should not exceed the benefit of the information [12].

The requirements on an EWS, analyzed from the perspectives of resilience, supply chain and EWS itself can be summarized as shown below:

- Resilience: identification and monitoring of risks, proactivity.
- Supply Chain: dynamic, parametric, adaptability, transparency, data acquisition of: delivery delays, material price, material availability, Tier 1 - Tier X, delivery routes, location of the supplier.
- EWS: unambiguity, completeness, timeliness, timely availability, economic viability, general applicability, integration capability.

2.2 State of the art

In order to analyze early warning approaches in the area of supply chain and to identify the related weaknesses, a systematic literature review was carried out. For this, two different data bases were used: Scopus and Leibnitz Information Center for Economics. First, the keyword used for the research was “early warning system”. With this term, 32,322 sources were identified. The restriction with the term "supply chain" reduced the sources to 190. The subsequent analysis of the text showed that the majority of the sources concern themselves with risk management strategies and not with an approach for an EWS. Only three papers refers to such an approach. The one described by Moder examines the necessary measures for identifying and analyzing risks in procurement. He also describes the extent to which the implementation of an EWS could be implemented [13]. Czaja works on an approach for an EWS to detect quality defects in purchased parts [2]. Genc develops an EWS for disruptions in the supply chain based on a supply chain reference model, in which disruptions are only identified and evaluated once they have occurred [14]. The analysis of existing approaches shows that the authors do not systematically consider the requirements of the supply chain. In addition, there is no consideration and definition of the warning point and warning limits. As a result, the approaches only warn when a disruption has already occurred. Furthermore, the focus is not on an EWS particularly for the area of procurement. The approach presented in this paper provides a solution to these issues.

3. Design of an EWS

The structure of the approach development is based on the stage model of an indicator-based early warning system according to Krysnek and the Knowledge Discovery in Databases (KDD) process [12, 15]. The procedure is described in Figure 3. The focus in this paper is on the design phase.

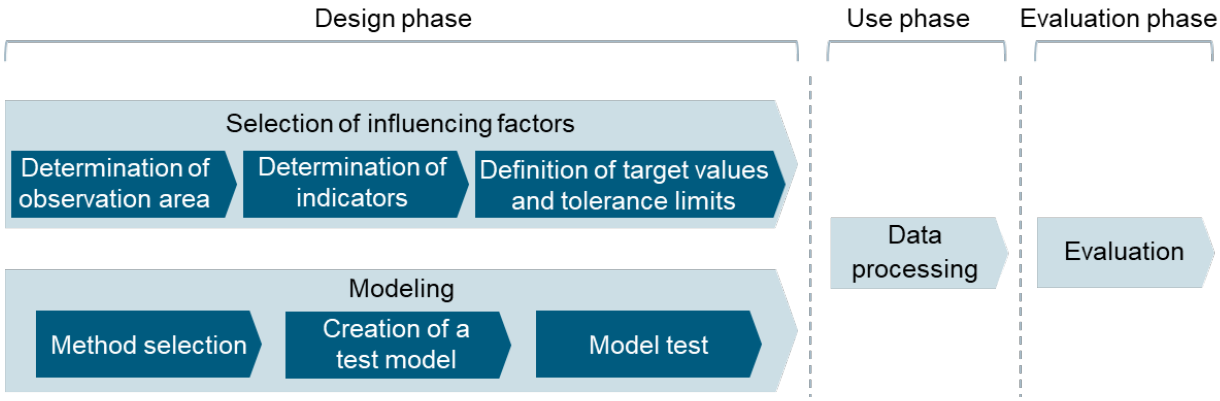


Figure 3: Procedure for model development

3.1 Selection of influencing factors

The observation framework is based on the analyzed risks and the basic requirements of an EWS. The emphasis is on risks outside the supply chain. To simplify the model, the focus is placed on three risks: transportation risks, material availability and political restrictions. The category of transport risks is, in turn, restricted to the consideration of sea routes. In the category of material availability, a distinction must be made between a general shortage and a price shift that is not related to availability. The focus of political risks is on the country of origin of the required raw material. In order to meet the requirements, the indices shown in Table 2 were identified for the individual indicators.

Table 2: Indicators for the identified risks

Indicator	Index	Description	Components
Risks of transportation	Global Supply Chain Pressure Index	Monitoring of transport route pressure based on a dimensionless number on the single-digit range, fluctuating around 0. A high value corresponds to high pressure.	Baltic Dry Index: freight rates for bulk goods; Harpex Index: charter rates for container ships, processed goods; Airfreight Cost Index: monitoring of airfreight costs
Availability of goods	Raw Material Index	Monitoring of the price development	Raw material
Political risks	Stability of the political system	Monitoring of political activities	Property rights, judicial effectiveness, government integrity, tax burden, fiscal health, business investment, employment investment, trade investment, financial, innovation autonomy, economy autonomy

In the final step of the selection of indicators, it is necessary to consider the warning point. The analysis of existing literature has shown that this aspect has not been taken into account in previous approaches. Due to the heterogeneity of the individual requirements of companies, it does not make sense to specify the warning point in general. Instead, it makes more sense to develop a model that maps the aspects to be considered. At the same time, the aim should be to reduce complexity in order to maximize the benefits. The model proposed in this paper is based on the factors influencing the ideal procurement time and is supplemented by the requirements from risk management to increase resilience. Figure 4 presents the model.

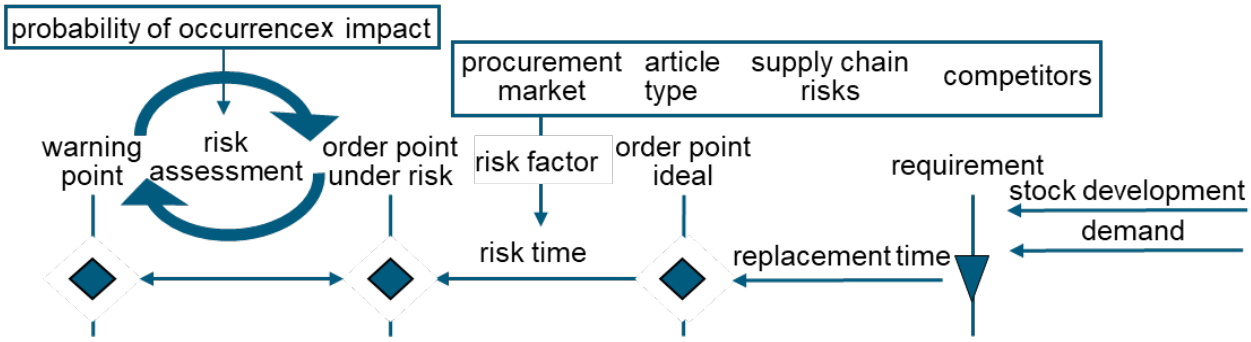


Figure 4: Model to detect warning point

The model is based on backward scheduling. Demand is determined on the basis of the stock development and demand. A distinction is made between actual and forecasted demand. Based on the demand, the ideal ordering point is determined via the replacement time without taking the risk into account. However, from the point of view of resilience, the order time is determined taking the risk into account. For this purpose, a risk factor must be determined, which is made up, for example, of the risks in the supply chain and other internal and external individual factors. This allows the determination of the warning point. The interaction between the warning point and the order point under risk must be considered. The earlier the warning is issued, the less meaningful it is, as less is known about the possible development of the situation. Therefore,

the warning must be evaluated under risk to determine the order point. To do this, it is advisable to multiply the probability of occurrence and the impact.

In addition to the warning time, the warning limit must also be defined specifically for each company and individually for each raw material category. On the one hand, internal factors such as company size and liquidity must be taken into account. The most important factor is the relevance of the raw material for the company, based on the impact of a disruption. The external factors result from the consideration of the related risks. Depending on the assessment of the factors, the warning limit should be set at different levels. For example, in the case of rare earths, the majority of which are found in China [16], the warning limit should be set significantly lower than for raw materials sourced from different countries. The number of substitutes must also be considered. Nickel is a suitable example: despite the discontinuation of Russian imports, there was still the possibility of importing the raw material from other countries.

3.2 Modeling

3.2.1 Method selection

Due to the requirements of the approach, the utilization of a machine learning (ML) method is suitable. ML aims to recognize correlations and patterns from input data and derive rules [17]. There are different approaches according to which the ML methods can be differentiated (see also [18]). Due to the selected indicators and the requirement for predictions in the case of non-specified labels, methods of unsupervised learning are suitable. In contrast to supervised learning, semi-supervised and reinforcement learning; this learning task is suitable for reducing distortions and finding anomalies in data sets. The algorithm determines whether data deviates significantly from other data. Furthermore, methods for solving classification tasks are suitable for this problem. In contrast to clustering, the group into which an object can be categorized is already known [17]. This involves the analysis of features that can be used to make the classification. This results in the requirement for a method that fulfills the learning task of classification and meets the learning task of unsupervised learning. Methods based on a decision tree were excluded [17], as they focus on the identification of decisions, which is not suitable for an EWS. However, it would be possible to use the method in further research steps. The Principal Component Analysis (PCA) is suitable, considering the requirements mentioned above. In classic PCA, correlating influencing factors are reduced to a few non-correlating principal components [17]. The resulting reduction in dimensions makes it possible to limit the number of indicators and thus enable interpretation. Only implementing PCA is not sufficient for an EWS, additional steps are required. Using the method, the approach of the EWS is divided into six steps: 1) identification of the main components, 2) analysis of the behavior of the main components over time, 3) identification of past disturbances in the observation area, 4) analysis of the effects on the observation over time, 5) analysis of the dependencies between the indices and 6) constant monitoring of the indices in a software tool observing if the warning limits are exceeded.

3.2.2 Creation of a test model

The test model was set up using Python programming. The method is tested using the raw material nickel, which is suitable due to the large number of disruptions in recent years. For example, sanctions against Russia led to disruptions on the nickel market [19]. Before the analysis could be carried out, a database was set up and the data from the indices was cleansed. Arithmetic means were calculated to eliminate data gaps.

3.2.3 Model test

The first analysis of the correlation between the price development of nickel and the raw material index already shows a conspicuous correlation at the time the disruptions occurred. This is shown in red in Figure 5. The disruption in 2019 can be explained by an embargo in Indonesia, the disruption in 2022 by the sanctions against Russia [19, 20].

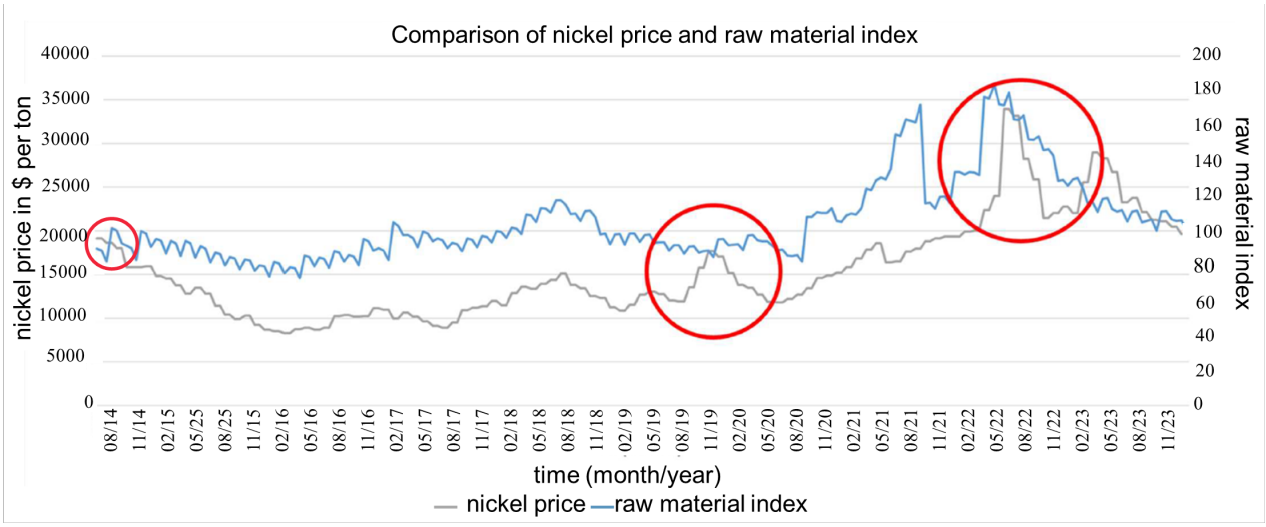


Figure 5: comparison of nickel price and raw material index over time

If the defined requirements of an EWS are to be met, the statement regarding the correlation alone is not sufficient. The EWS requires an analysis of the changes prior to the disruption. The analysis using the supply chain pressure index did not reveal any anomalies. This was to be expected, as there is no direct correlation between the type of disruption (political in nature) and the components contained in the index. These relate primarily to transportation costs. However, including indicators for the determination of the stability of the political system reveal changes previous to the disruption. The result of the principal component analysis is shown in Figure 6. Figure 6a contains the analysis for nickel from Russia, Figure 6b for nickel from Indonesia.

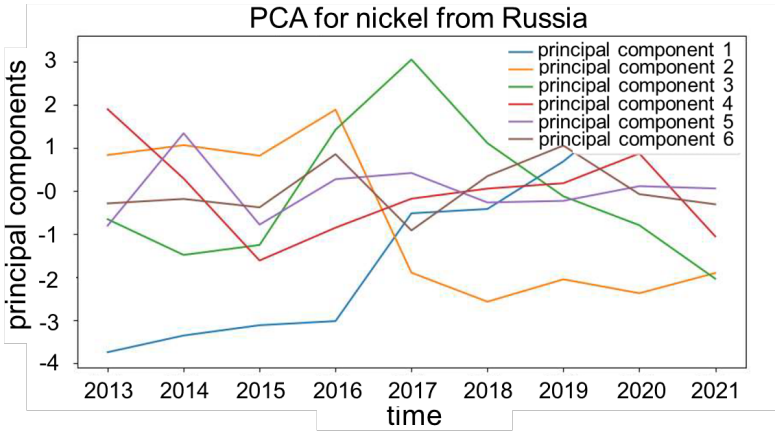


Figure 6a: PCA for nickel from Russia

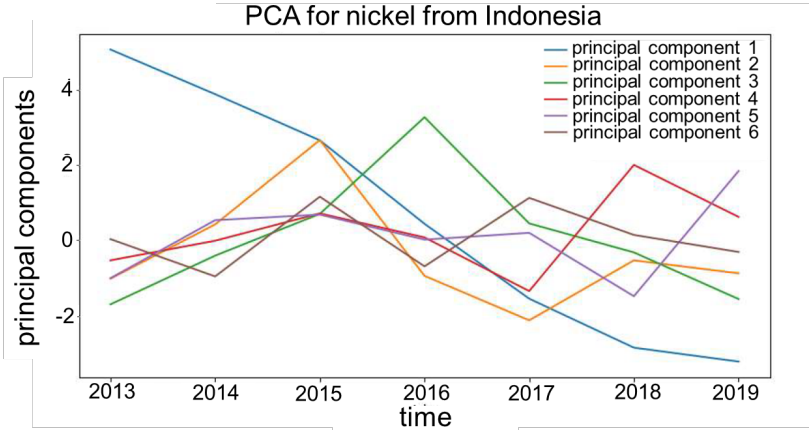


Figure 6b: PCA for nickel from Indonesia

The result of the model test shows that there is a correlation between negative trends in the considered data and the subsequent occurrence of the disruption. It could therefore be inferred that it is possible to identify a disruption at an early stage by applying the PCA method to the three indicators.

4. Conclusion and Outlook

The crises of the last four years have increasingly highlighted the vulnerability of supply chains. A fast response time is required to ensure the ability of companies to deliver. The reviewed literature on resilience calls for measures to prepare for a crisis. For this purpose, this paper proposes an EWS that considers the procurement risks in supply chains to identify potential crises at an early stage. A systematic literature review to identify weak points of existing EWS approaches has shown that of 190 identified sources, only three authors describe a methodic approach. Furthermore, the analysis of these approaches has shown that the authors do not systematically consider the requirements of the supply chain. In addition, the approaches only warn when a disruption has already occurred, due to the missing consideration and definition of the warning point and warning limits. Moreover, none of the presented EWS approaches focuses in particular on the area of procurement. The approach proposed in this paper differs from previous work in that the supply chain requirements on an EWS have been systematically worked out and the system warns of possible disruptions at an early stage, before a disruption occurs. Particular attention was placed on the aspect of early warning. It was pointed out that no general warning point can be defined for an EWS; instead, it must always be considered in the context of the company. To this end, a model was presented depending on the risk and replacement times. The presented concept is based on two main steps: the selection of influencing factors and the modeling. To select the indicators, the area under consideration was first narrowed down using the risk categories, also paying attention to the free availability of the indicators. Three indicators were identified for predicting disruptions on the procurement side: supply chain pressure index, raw material index and stability of political system. The requirements of an EWS and the nature of the indicators led to a method from ML. The approach presented is based on a Principal Component Analysis. The model test for the raw material nickel shows that this method would allow to identify a potential disruption before it occurs based on the selected indices. However, in order to be meaningful, it is necessary to apply the approach to other raw materials and also to validate it with industry partners.

Further steps are necessary for this: In the first step, the validation should be tested using further data sets and, if necessary, combined with further ML procedures to improve the results. This would also enable the validation with industrial companies. Working with industry partners would make it possible to take earliness and warning limits from the praxis into account. However, this would also require preparation of the company data. First of all, it would be necessary to narrow down the area under consideration. This includes the selection of the raw materials. The results can then be used to calculate the warning point and the warning limits. A particular challenge here is the necessary transparency in the supply chain. Companies need to know exactly where the raw materials are sourced from. The more knowledge available about the Tier 1 supplier, the more accurately a disruption can be predicted.

Acknowledgements

The research presented in this paper was supported by the European Commission through the H2020 project EPIC (https://www.centre-epic.eu/) under grant No. 739592. This project has received funding from the European Union's Horizon 2020 research and innovation programme under grant agreement No 873086. The authors are responsible for the content of this publication.

References

[1] M. Lütke and D. Goetjes, "Wie robust ist die Supply Chain aufgestellt?," *Deutsche Molkerei Zeitschrift*, no. 15, pp. 21–23, 2022.

[2] L. Czaja, *Qualitätsfrühwarnsysteme für die Automobilindustrie*. Zugl.: Erlangen-Nürnberg, Univ., Diss., 2008 u.d.T.: Einsatz und Bedeutung von Qualitätsfrühwarnsystemen zur Unterstützung des Supply Chain Risk Management in automobilen Wertschöpfungsnetzwerken : eine empirische Untersuchung in der deutschen Automobilindustrie, 1st ed. Wiesbaden: Gabler, 2009.

[3] D. Ivanov, *Einführung in die Widerstandsfähigkeit der Lieferkette: Management, Modellierung, Technologie*. Cham: Springer International Publishing; Imprint Springer Gabler, 2023.

[4] T.-F. Hinrichsen, E. Colangelo, and T. Bauernhansl, "Function-based Approach for Supply Chain Resilience," *Procedia CIRP*, vol. 120, pp. 219–224, 2023, doi: 10.1016/j.procir.2023.08.039.

[5] A. Thom, *Entwicklung eines Gestaltungsmodells zum Management von Risiken in Produktionsnetzwerken: Ein Beitrag zum Risikomanagement in der Logistik*. Zugl.: Berlin, Techn. Univ., Diss., 2007, 1st ed. Berlin: Univ.-Verl. der Techn. Univ, 2008.

[6] A. Ziegenbein, Ed., *Supply Chain Risiken: Identifikation, Bewertung und Steuerung*. Zugl.: Zürich, Eidgen. Techn. Hochsch., Diss., 2007, 1st ed. Zürich: vdf Hochschulverl. an der ETH, 2007. [Online]. Available: http://bvbr.bib-bvb.de/F?func=service&doc_library=BVB01&doc_number=016151056&line_number=0002&func_code=DB_RECORDS&service_type=MEDIA

[7] A. Prinz, "Mathematische Modellierung zur Optimierung der Wertschöpfungsverteilung nach quantitativen und qualitativen Kriterien in Produktionsnetzwerken der diskreten Fertigung," Dissertation, Fraunhofer-Institut für Produktionstechnik und Automatisierung.

[8] Gabler Wirtschaftslexikon, *Frühwarnsysteme.* [Online]. Available: https://wirtschaftslexikon.gabler.de/definition/fruehwarnsysteme-33743 (accessed: Mar. 7 2024).

[9] F. Neske, Ed., *Management-Lexikon*. Gernsbach: Dt. Betriebswirte-Verl.

[10] C. Dreger and K. A. Kholodilin, "Spekulative Preisentwicklung an den Immobilienmärkten: Elemente eines Frühwarnsystems," *DIW Wochenbericht*, 37/38, pp. 2–9, 2011.

[11] S. Hauff, "Konzeption der Früherkennung," *Diskussionspapiere des Schwerpunktes Unternehmensführung am Fachbereich BWL der Universität Hamburg*, no. 02, 2009.

[12] U. Krystek, "Krisenarten und Krisenursachen," in *Krisenmanagement: Grundlagen, Strategien, Instrumente*, T. Hutzschenreuter, Ed., 1st ed., Wiesbaden: Gabler, 2006, pp. 41–66.

[13] M. Moder, *Supply Frühwarnsysteme: Die Identifikation und Analyse von Risiken in Einkauf und Supply Management*. Wiesbaden: Betriebswirtschaftlicher Verlag Dr. Thomas Gabler / GWV Fachverlage GmbH Wiesbaden, 2008.

[14] E. Genc, *Frühwarnsystem für ein adaptives Störungsmanagement*. Zugl.: München, Techn. Univ., Diss., 2015. München: Utz Herbert, 2015.

[15] U. Fayyad and Piatetsky-Shapiro, Gregory, Smyth, Padhraic, "From Data Mining to Knowledge Discovery in Databases," *AI Magazine*, no. 3, 1996.

[16] B. Eyssel, *Wertvolle Rohstoffe: Wo gibt es die meisten Seltenen Erden?* [Online]. Available: https://www.tagesschau.de/wirtschaft/weltwirtschaft/seltene-erden-korrikette-101.html (accessed: Mar. 13 2024).

[17] I. Döbel *et al.,* "Maschinelles Lernen – Kompetenzen, Anwendungen, und Forschungsbedarf," 2018.

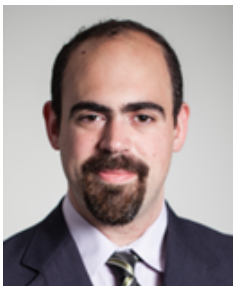
[18] A. Jung, *Maschinelles Lernen: Die Grundlagen,* 1st ed. Singapore: Springer Nature Singapore; Imprint Springer, 2024.

[19] J. Blume, F. Hubik, and S. Menzel, *„Ausfall Russlands ist die größte Sorge für die Batterie-Lieferkette“ – Nickel gefährdet den Elektro-Boom.* [Online]. Available: https://www.handelsblatt.com/unternehmen/industrie/ukraine-krieg-ausfall-russlands-ist-die-groesste-sorge-fuer-die-batterie-lieferkette-nickel-gefaehrdet-den-elektro-boom/28178188.html (accessed: Mar. 19 2024).

[20] N. Mahlke, *Welthandelsorganisation kippt Ausfuhrverbot für Nickelerz.* [Online]. Available: https://www.gtai.de/de/trade/indonesien/branchen/welthandelsorganisation-kippt-ausfuhrverbot-fuer-nickelerz-926814

Biography

Theresa-Franziska Hinrichsen (*1994) studied Industrial Engineering and Business Administration in Hamburg and Mannheim. Since 2021, she is a research fellow with focus on production planning and control with a focus on digitalization and resilience at the Fraunhofer Institute for Manufacturing Engineering and Automation IPA.



Eduardo Colangelo (*1986) studied Industrial Engineering in Buenos Aires, subsequently gaining a doctoral degree from the University of Stuttgart. He has been working as a research fellow at the Fraunhofer Institute for Manufacturing Engineering and Automation IPA since 2013, occupying the position of deputy leader of the group Digital Order Management since 2023.

Adrian Wrobel (*1997) studies production technology and management in Hamburg and worked as a student research assistant at the Fraunhofer Institute for Manufacturing Engineering and Automation IPA.