Root Cause Analysis for Manufacturing using Semantic Web Technologies

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Abstract
Root Cause Analysis is a method to identify the cause of problems in manufacturing. The analysis is usually performed manually by experts, is time-consuming, and costly. Therefore, the automation of the analysis process is of interest. However, besides measurements from manufacturing processes, prior knowledge is needed to create results comparable to those from manual analysis. This work uses Semantic Web technologies to model prior knowledge and Neuro-Symbolic AI to reason for root causes. The Neuro-Symbolic AI combines reasoning on observed production data and on prior knowledge. Using such approach makes it possible to combine efficient pattern recognition and probabilistic reasoning for data analysis. This work shows an evaluation workflow for such proposed methods with a data generation model. Preliminary results show the conceptualization of available prior manufacturing knowledge. The future steps contain the research on data models and the evaluation of existing Neuro-Symbolic approaches.

Keywords
Neuro-Symbolic AI, Root Cause Analysis, Knowledge Graph

1. Introduction

Enabling high quality and efficiency simultaneously in manufacturing is a challenging task. Root Cause Analysis (RCA) is used for identification of problems in manufacturing to reduce machine downtimes and the amount of produced scrap. The aim is to find and fix the cause of a problem rather than treat the symptoms [1]. However, current methods depend highly on expert knowledge, like the Failure Mode and Effect Analysis, the Ishikawa Diagram, or the 5-Why Analysis [2]. Since traditional RCA is an expert-dependent and time-consuming process, automating RCA is a research topic of interest. Furthermore, the usage as an on-production-line analysis tool [3] and the incorporation of additional observed data [4] motivate the automation of RCA.

The proposed research aims to integrate prior knowledge into an automated RCA process. Therefore, the advantages of symbolic and sub-symbolic methods should be combined. Such Neuro-Symbolic approaches use the pattern recognition capabilities of neural approaches and the first-order logic from symbolic approaches [5].

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Performing RCA requires data from different sources. Semantics are essential in integrating this data since the same concepts are often named differently across different datasets. Another crucial part of the data collection is documenting and integrating data sources into a common framework [6]. Semantic Web (SW) technologies can deal with these data integration challenges and are already highly used in smart manufacturing for cyber-physical production systems, as overviewed by Sabou et al. [7]. Using the standards from SW enables the extensibility and compatibility of modeled knowledge. As expected by Hitzler et al. [8], interoperable standards like the Resource Description Framework and the Web Ontology Language from SW are of interest for research in the domain of Neuro-Symbolic methods. Promoting the standards from SW for use in Neuro-Symbolic Artificial Intelligence methods, therefore, helps strengthen SW community efforts and improves compatibility of researched solutions.

2. Related Work

2.1. SW Technologies for RCA

Abele et al. [9] use ontologies for an alarm RCA in manufacturing. For this application, they store expert knowledge about abnormal machine situations and incorporate data from structured failure analysis of processes (like Failure Mode and Effect Analysis) to perform probabilistic reasoning. Besides incorporating structured failure analysis data, ontologies can model hierarchical dependencies in assembly groups to track occurring failure paths on a component location level ([10], [11]). The summarized RCA methods aim to find a root cause's location and time. Oliveira et al. [4] name this RCA level Location-Time. The more precise RCA level Physical, according to Oliveira et al. [4], investigates the root cause on a physical process parameter level (e.g., "Force F led to the failing quality check"). Current methods for RCA on parameter level (e.g., like with Causal Artificial Intelligence [12]) do not use prior knowledge about relations and parameters in a general applicable, systematic way to enhance the analysis performance of RCA.

2.2. Neuro-Symbolic Artificial Intelligence

Pearl [13] gives in his work about causality three levels of causal hierarchy: Associational, interventional, and counterfactual. Pearl states neural network approaches can only perform association-level causality [13]. Based on this, Garcez and Lamb [5] see a need for combining symbolic approaches, capable of all three levels described by Pearl, with the pattern recognition capabilities of a neural approach. Incorporating symbolic knowledge for decision-making has the potential to enable better explainable decisions [14]. When contradicting or uncertain information is present, Probabilistic Reasoning [15] is of interest, where a possible representation is the Markov Logic Network (MLN). MLNs utilize weights to transform hard constraints about assumptions into soft constraints [16]. Qu and Tang [17] combine Markov Logic Networks with Knowledge Graph Embeddings to a Neuro-Symbolic approach called pLogicNet. Another Neuro-Symbolic method incorporating Probabilistic Reasoning is DeepProbLog: Neural Probabilistic Logic Programming [18], which enables using neural networks and probabilistic-logic reasoning

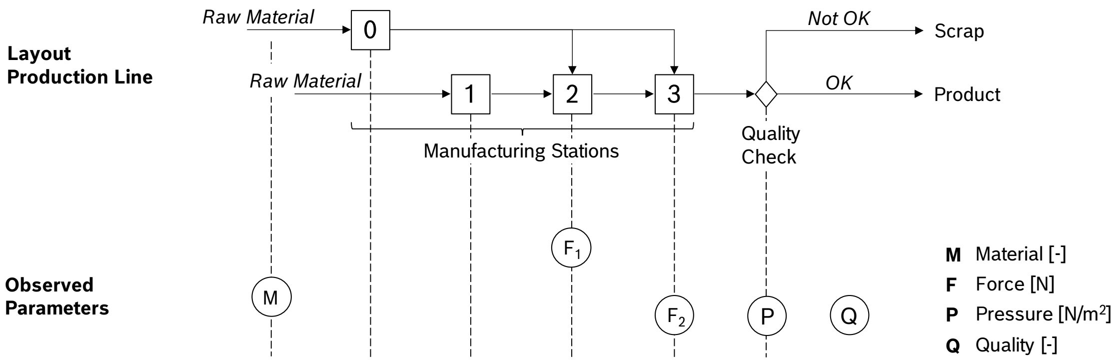

Figure 1: Schema of a production line with different production stations and a quality check

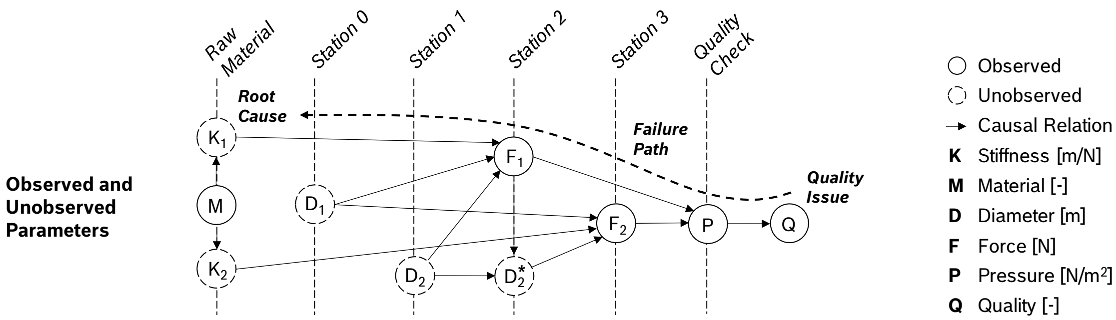

Figure 2: A failure path over multiple causal relations of observed and unobserved parameters

in a common framework. Therefore, probabilistic reasoning incorporates the uncertainty about the output of a neural network.

3. Problem Statement

To illustrate the problem a production line with four stations manufacturing a product is given (see Figure 1). While at station 2 and station 3 a fitting process of two components is performed, sensors record the observable production parameters force F_1 and force F_2. At the end of the line, a quality check measures the tightness of the produced fitting with a pressure P as a product feature used to compute a quality label Q using tolerance limits. In addition to continuous data, categoric parameters of used raw materials (in Figure 1 material M), produced products, utilized machines, or executed control programs are available. A typical application example of RCA is to identify the most likely parameter(s) that caused a failed quality check.

The causal relations describe influences between different parameters. A failure path consists of a row of causal relations and origins from a failing quality check. The end of a found failure path is a root cause. For example, in Figure 2 the raw material stiffness K is most likely the cause of the failing quality assessment, but also multiple combined root causes for one occurring quality issue are possible. For analyzing the likelihood of parameters being a root cause, the causal relations of parameters to the final quality check play an important role. Therefore, empirical models can be derived from observed production data via statistical learning to describe the influence of causal relations between observed parameters. However, such empirical models' performance is limited in manufacturing due to data quality issues like long-tail distributions and missing data for failure situations [19]. That leads to bad out-of-distribution generalization of empirical models. As shown in Figure 2, unobserved parameters in manufacturing can influence observed parameters via a causal relation and hence change the functional relationship between the observed parameters. Therefore, unobserved parameters make using statistical models hard. Instead, prior knowledge from experts or laboratory experiments investigating the effect of certain unobserved parameters, causal relations, or physical models could improve the performance of the analysis. Confidence evaluations about the validity of a model or an assumption for a certain parameter range are gained by laboratory experiments. However, it has yet to be proven how a Neuro-Symbolic RCA could use such prior knowledge which could be contradicting or uncertain.

Hypothesis. Neuro-Symbolic methods using prior manufacturing domain knowledge about causal relations and parameter models integrated with a Knowledge Graph improve the RCA performance on observed production data. In the following, three research questions are posed to prove this hypothesis.

RQ1. Which prior knowledge from manufacturing supports RCA, and how to integrate this knowledge into a common Knowledge Base to enable neuro-symbolic RCA? This research question includes research on existing data sources from manufacturing and on already available data from traditional RCA methods like Failure Mode and Effect Analysis.

RQ2. How to combine symbolic and sub-symbolic methods to improve the performance of RCA methods in manufacturing using prior knowledge? The proposed methods use prior knowledge and are capable of learning hidden data patterns. The methods aim to find failure paths within the Knowledge Graph and uncover the root cause of an observed quality problem.

RQ3. How to perform RCA on contradicting or uncertain information? The developed methods infer conclusions on sets of contradicting or uncertain information so that the RCA is supported best in finding the most likely failure path within the Knowledge Graph structure.

4. Methodology and Approach

The following chapter gives an overview about methods and approaches used for researching the posed questions.

RQ1. A ground-truth data generation model is developed to generate observable data

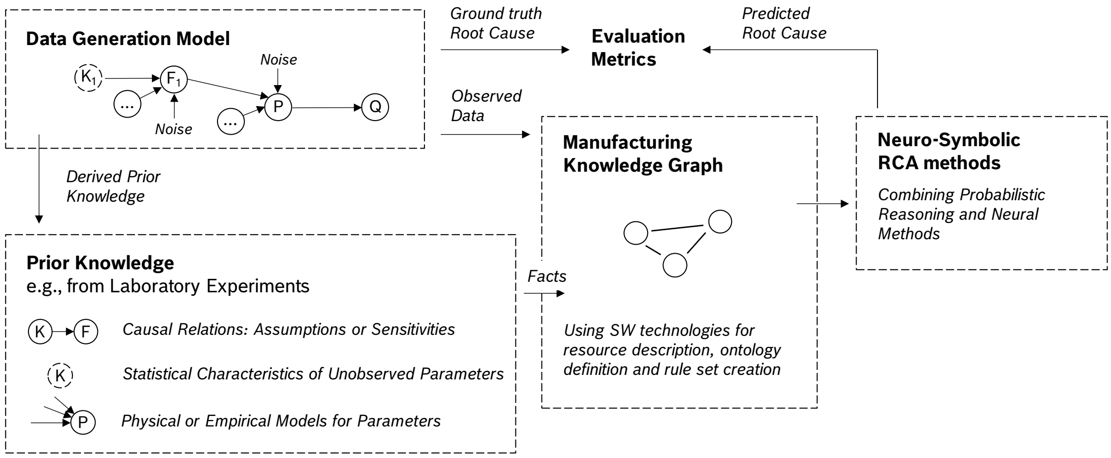

Figure 3: An overview of the workflow for evaluation of Neuro-Symbolic RCA methods

and derive a varying amount of prior knowledge (see Figure 3). By assuming different degrees of prior knowledge, it could be identified which information has the potential to improve RCA performance. SW technologies are used with developed data models to integrate the data. The data model design describes a generally applicable schema for prior knowledge in the manufacturing context and is optimized for efficient use with proposed RCA methods.

RQ2. Proposed RCA methods follow a graph-traversal approach and investigate a parameter and its causal relations to other parameters to select a parameter that is most likely part of a failure path. Information about causal relations could be captured in prior knowledge (like expert assumptions or sensitivity analysis) or hidden within historical observed production data (data containing information about causal relations). A sub-symbolic approach makes use of hidden data patterns and handles noise of observed production data, while a symbolic approach combines results from sub-symbolic methods with prior knowledge stored in a Knowledge Graph.

RQ3. The MLN is a probabilistic representation of interest for reasoning on soft constrained information. Integrating such probabilistic representations into neural approaches like those proposed with pLogicNet by Qu and Tang [17] and DeepProbLog by Manhaeve et al. [18] is of special interest. Evaluating such integrations for use in the context of RCA, but also improvements of those, should be researched. The probabilistic approach incorporates rules and probabilities into the root cause search.

5. Evaluation Plan

The evaluation of the proposed methods takes place using benchmark datasets. As shown in Figure 3, a benchmark dataset consists of synthetically generated production data utilizing a

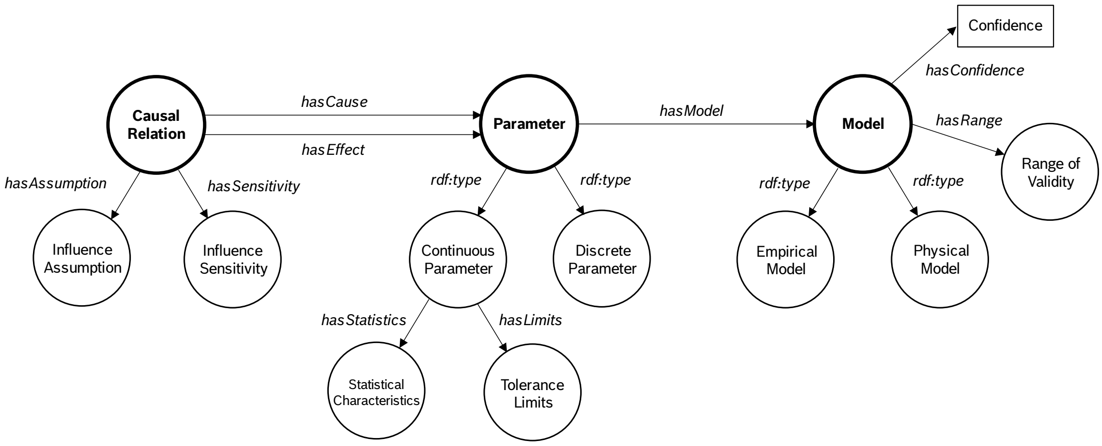

Figure 4: The concept for an ontology modeling prior knowledge about manufacturing data

data generation model. The data generation model uses the underlying physical models of a manufacturing process to generate data samples. Therefore, the input parameters of this data generation model sample their values from a pre-defined distribution. On all observed parameters, noise is added according to the uncertainty of the measurement procedure. While the underlying physical model builds a realistic process for synthetic data generation, knowledge on its structure and used physical models is assumed to be only partially available for the RCA methods developed and evaluated as part of this work. Also, only some parameter values are assumed to be observed. Unknown values represent unobserved parameters in production lines. Root causes can be injected systematically, and a ground truth for evaluation of the RCA is therefore available.

The workflow in Figure 3 shows how synthetically generated data is integrated into a shared Knowledge Graph along with prior knowledge. Using the integrated knowledge, Neuro-Symbolic RCA methods are used for reasoning for failure paths and root causes. The measurement of the performance of proposed methods takes place using performance metrics. Computed metrics include accuracy for outputting the correct root cause. In addition, the evaluation uses top-k accuracy metrics for different set sizes k. The top-k metric measures how often the correct root cause is within the set of most likely outputted k predicted root causes. Of interest for comparison are benchmark datasets that use a purely data-driven RCA approach (e.g., [12]).

6. Preliminary Results and Next Steps

This work is in its first year, and the primary efforts made so far were conceptualizing the problem domain. Therefore, investigations on available prior knowledge for integration into a common Knowledge Graph like shown in Figure 3 were made. Figure 4 shows the three main concepts: parameters, causal relations, and parameter models.

A parameter can therefore be discrete or continuous. Statistical characteristics and tolerance limits could be prior knowledge for continuous parameters from lab experiments during process development. Prior knowledge about causal relations is present in expert assumptions (e.g., K proportional F) or analyzed sensitivities from sensitivity studies. In this context, a parameter model describes a parameter based on its incoming causal relations. These models can be of two types. The first type is an empirical model, which is derived from observed historical data, and the second type is a generally applicable physical model. A parameter could have multiple associated models, that could be rated with confidences and parameter ranges for their validity.

The next step is to specify an ontology from the first concept made in Figure 4 and then to generate a suitable benchmark dataset with the shown workflow in Figure 3. In the following, existing Neuro-Symbolic approaches using probabilistic reasoning (like [17], [18]) are evaluated to incorporate available prior knowledge into RCA.

7. Conclusion

This research proposal shows the motivation for Neuro-Symbolic RCA methods using SW technologies for automating RCA in manufacturing. The problem statement describes the concept of the manufacturing line with observables and prior knowledge. Proposed approaches are SW technologies for data integration and Neuro-Symbolic methods with probabilistic reasoning for RCA. For the evaluation, a workflow is described using a ground-truth data generation model, to compute performance metrics for proposed methods. The first preliminary results show a concept for describing the ontology of prior knowledge from manufacturing. This work generally contributes to using SW technologies for Neuro-Symbolic methods and Neuro-Symbolic RCA in manufacturing. Potentially, synergies and challenges for using SW technologies in Neuro-Symbolic Artificial Intelligence will evolve from this research.

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References

[1] T. Ōno, Toyota production system: beyond large-scale production, Productivity Press, Cambridge, Mass, 1988.

[2] P. Chemweno, L. Pintelon, L. Jongers, P. Muchiri, i-RCAM: Intelligent expert system for root cause analysis in maintenance decision making, IEEE, 2016, pp. 1–7. URL: http://ieeexplore.ieee.org/document/7542830/. doi:10.1109/ICPHM.2016.7542830.

[3] L. Rokach, D. Hutter, Automatic discovery of the root causes for quality drift in high dimensionality manufacturing processes, Journal of Intelligent Manufacturing 23 (2012) 1915–1930. URL: http://link.springer.com/10.1007/s10845-011-0517-5. doi:10.1007/s10845-011-0517-5.

[4] E. e Oliveira, V. L. Miguéis, J. L. Borges, Automatic root cause analysis in manufacturing: an overview & conceptualization, Journal of Intelligent Manufacturing (2022). URL: https://link.springer.com/10.1007/s10845-022-01914-3. doi:10.1007/s10845-022-01914-3.

[5] A. d. Garcez, L. C. Lamb, Neurosymbolic AI: The 3rd Wave, arXiv, 2020. URL: https://arxiv.org/abs/2012.05876, dOI: 10.48550/ARXIV.2012.05876.

[6] V. Sugumaran, J. A. Gulla, Applied semantic web technologies, CRC Press, 2011.

[7] M. Sabou, S. Biffl, A. Einfalt, L. Krammer, W. Kastner, F. J. Ekaputra, Semantics for cyber-physical systems: A cross-domain perspective, Semantic Web 11 (2020) 115–124.

[8] P. Hitzler, F. Bianchi, M. Ebrahimi, M. K. Sarker, Neural-symbolic integration and the Semantic Web, Semantic Web 11 (2020) 3–11.

[9] L. Abele, M. Anic, T. Gutmann, F. Jens, K. Martin, V.-H. Birgit, Combining Knowledge Modeling and Machine Learning for Alarm Root Cause Analysis, in: IFAC Proceedings Volumes (IFAC-PapersOnline), volume 46, 2013. doi:10.3182/20130619-3-RU-3018.00057.

[10] A. Zhou, D. Yu, W. Zhang, A research on intelligent fault diagnosis of wind turbines based on ontology and FMECA, Advanced Engineering Informatics 29 (2015) 115–125. URL: https://linkinghub.elsevier.com/retrieve/pii/S1474034614000962. doi:10.1016/j.aei.2014.10.001.

[11] M. Hu, Y. Liu, V. Sugumaran, B. Liu, J. Du, Automated structural defects diagnosis in underground transportation tunnels using semantic technologies, Automation in Construction 107 (2019) 102929. URL: https://linkinghub.elsevier.com/retrieve/pii/S0926580518306538. doi:10.1016/j.autcon.2019.102929.

[12] K. Budhathoki, L. Minorics, P. Bloebaum, D. Janzing, Causal structure-based root cause analysis of outliers, in: K. Chaudhuri, S. Jegelka, L. Song, C. Szepesvari, G. Niu, S. Sabato (Eds.), Proceedings of the 39th International Conference on Machine Learning, volume 162 of *Proceedings of Machine Learning Research*, PMLR, 2022, pp. 2357–2369. URL: https://proceedings.mlr.press/v162/budhathoki22a.html.

[13] J. Pearl, The seven tools of causal inference, with reflections on machine learning, Communications of the ACM 62 (2019) 54–60.

[14] A. Oltramari, J. Francis, C. Henson, K. Ma, R. Wickramarachchi, Neuro-symbolic Architectures for Context Understanding, arXiv, 2020. URL: https://arxiv.org/abs/2003.04707, dOI: 10.48550/ARXIV.2003.04707.

[15] J. Pearl, Probabilistic reasoning in intelligent systems: networks of plausible inference, Morgan kaufmann, 1988.

[16] M. Richardson, P. Domingos, Markov logic networks, Machine learning 62 (2006) 107–136.

[17] M. Qu, J. Tang, Probabilistic Logic Neural Networks for Reasoning, in: Advances in neural information processing systems, 2019.

[18] R. Manhaeve, S. Dumančić, A. Kimmig, T. Demeester, L. D. Raedt, DeepProbLog: Neural Probabilistic Logic Programming, 2018.

[19] Y. Wilhelm, P. Reimann, W. Gauchel, B. Mitschang, Overview on hybrid approaches to fault detection and diagnosis: Combining data-driven, physics-based and knowledge-based models, Procedia CIRP 99 (2021) 278–283. URL: https://linkinghub.elsevier.com/retrieve/pii/S2212827121003152. doi:10.1016/j.procir.2021.03.041.