Analysis of Quality Issues in Production With Multi-view Coordination Assets ⋆

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Abstract: The diffusion of the Industry 4.0 paradigm has led to a proliferation of data that is generated by production assets on the shop floor. This data opens up new opportunities for the analysis of quality issues, but it also makes identifying, selecting, and correctly interpreting data all the more critical. This involves a multitude of domain experts that design, operate and maintain production equipment. Major challenges they face in this context are (i) to map and integrate their domain knowledge on potential failure modes and effects, products, processes and production assets; and (ii) to coordinate their actions to systematically investigate and address the most important issues first. To address these challenges, this paper introduces the *FMEA-linked-to-PPR Asset Issue Analysis (FPI) Model*, a multi-view coordination asset, to guide quality issue analyses. The model integrates cross-domain knowledge and facilitates tracking the investigation state of quality analyses in teams of domain experts. A preliminary evaluation on a real-world use case indicates the FPI model to facilitate effective cross-domain analytic processes and the efficient identification of potential causes for quality issues.

Keywords: Knowledge management in production, Quality management, Monitoring of product quality and control performance, Multi-view modeling of manufacturing operations

1. INTRODUCTION

The automotive industry and its supplier networks have established various standards such as ISO/TS 16949:2009 (ISO Central Secretary, 2009) to ensure high product quality along the production chain. Achieving the required high product quality consistently in the context of increasingly complex products is challenging. Consequently, the capability to find causes of quality issues in increasingly complex production processes efficiently is crucial to produce high quality products, increase equipment effectiveness, and reduce the risk of unplanned cost.

Resolving quality issues in modern production plants requires capabilities to integrate and analyze knowledge distributed over various engineering domains. The domains use various methods, heuristics and documentation artifacts to tackle the investigation from different angles. Yet, the capabilities to coordinate these views and facilitate the collaboration in knowledge intensive processes are currently insufficient (Santos França et al., 2015).

This shortcoming raises the following research questions (RQs): *(i)* How can a model-based approach facilitate knowledge collection and sharing among heterogeneous stakeholders to improve the analysis of quality issues in production? *(ii)* How can a knowledge-based approach guide domain experts in the cooperative analysis of quality issues in production?

This paper extends the Quality Dependency Graph (QDG) (Kropatschek et al., 2021), a multi-view coordination artifact (Biffl et al., 2021), to improve quality issue analysis by addressing the following requirements elicited with domain experts: *(i)* explicit representation and integration of heterogeneous domain knowledge to facilitate knowledge sharing, *(ii)* mapping of failure modes and effects to production processes, resources and products, and *(iii)* effective analysis support to locate production equipment components that are likely to cause a major quality issue.

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Based on the collected requirements, we developed the FMEA-linked-to-PPR Asset Issue Analysis (FPI) approach to inform quality issue analyses *(i)* by providing a foundation for efficient cross-domain knowledge sharing, *(ii)* by facilitating cross-domain collaboration through propagating investigation state markers in the model, and *(iii)* by linking causes and failure modes to production assets and their properties to locate causes at assets.

To evaluate the introduced approach, we conducted a feasibility study focused on the real-world use case *laser beam welding*, a widely used and crucial process in the automotive industry (Kacar et al., 2016). This use case is a salient example of a complex process in which quality issue analysis is inherently difficult, as the weld seam quality depends on a wide range of interdependent factors.

The remainder of this paper is structured as follows. Section 2 introduces the state-of-the-art concerning the field of research. Section 3 presents the use case *weld seam quality*. Section 4 introduces our analysis model for quality issues. Section 5 summarizes the evaluation results based on a feasibility study. Section 6 discusses research results and concludes the paper.

2. STATE OF THE ART

The need of manufacturers to increase product quality and maintain high overall production effectiveness motivated the development of various methodologies to support the identification and mitigation of production risks.

Failure Mode and Effect Analysis (FMEA) (Stamatis, 2003) is a well-established approach to discover and analyze risky issues in production and identify appropriate resolution actions. FMEA follows a systematic process that various domain experts typically conduct in close collaboration. The methodology has been widely adopted in many engineering scenarios. However, FMEA projects are mostly conceived as a "boring and complicated human activity" (Wu et al., 2021) to satisfy engineering regulations rather than a living model to improve production. Further, FMEA documents in spreadsheets make it difficult to maintain and use the collected domain knowledge.

Quality Function Deployment (QFD) is a systematic procedure to gather customer requirements and link them to product features and process characteristics. The approach has proven suitable to increase costumer satisfaction and reduce faults (Almannai et al., 2008), but it has similar drawbacks as the FMEA as collecting customer, competitor and engineering data across domains is a time-consuming and difficult task (Andronikidis et al., 2009).

Both methodologies have been extended and used in conjunction (Sivasamy et al., 2016; Wu et al., 2021; Almannai et al., 2008); these extensions fulfill the need for reproducibility and more rigorous process control. However, they do not focus on coordinating cross-domain diagnostic processes. Further, only recently approaches have emerged that combine data- and model-driven approaches for quality issue analyses (Filz et al., 2021).

This paper aims to contribute towards filling this gap by introducing a method building on a model of multi-view domain engineering knowledge that associates processes, products and resources with failure modes (Kropatschek et al., 2021; Biffl et al., 2021). The method builds on the representation of functional knowledge in systems engineering as formalized in VDI 3682 (2005), which provides a formal notation for product, production processes, and resources, i.e., machines. The resulting *FPI Model* explicitly represents heterogeneous domain knowledge a form that in machines cab interpret; this knowledge can be stored in a graph database and accessed by software modules to guide domain experts in complex quality issue analyses.

3. USE CASE WELD SEAM QUALITY

To identify suitable use cases and elicit requirements for the developed approach, two authors of this paper conducted a domain analysis at a major supplier of aluminium parts for the automotive industry in Europe.

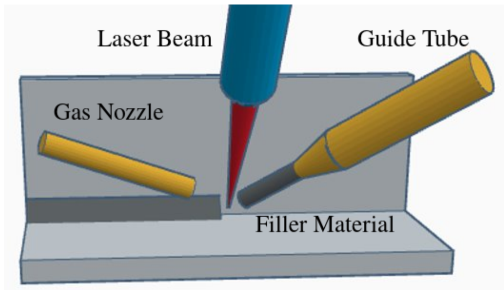

Fig. 1. High-level mechanics of *Laser Beam Welding*.

The use case *weld seam quality* (Kropatschek et al., 2021) involves a Cyber-physical Production System (CPPS) with machining and laser components to produce a structural part for a car. The identification of likely causes for failure modes that may affect the *weld seam quality* requires combining information on dozens of production assets and several hundred properties. This makes it difficult to efficiently address production challenges that require the collaboration of various domain experts with partial views.

Fig. 1 depicts a simple schematic of a laser welding process, consisting of *(i)* the *laser beam* to heat the material to join two pieces, *(ii)* a *guide tube* to supply *filler material*, and *(iii)* a *gas nozzle* to provide the welding gas that creates a gas shield to prevent oxidation or premature aging. The gas shield alignment is key to maintaining a consistent laser welding penetration depth (Katayama et al., 2010).

A large variety of factors can influence the quality of the weld seam. A mechanical engineer may, for instance, discover that a stained protection glass influences the laser power and, therefore, the weld seam. However, the mechanical view is only one perspective to discover possible dependencies. In practice, weld seam quality is affected by various physical effects, process deviations, resource dependencies, and many other unknown causes and failures. Consequently, the collaborative identification of causes of quality issues is a difficult and time-consuming process.

Welding Process Stakeholders. Quality issue analyses in automotive manufacturing are carried out by a set of stakeholders similar to those involved in production process engineering and operation (Meixner et al., 2021).

The *Quality Manager (QM)* creates or updates the FMEA and incorporates the inputs of other stakeholders. The

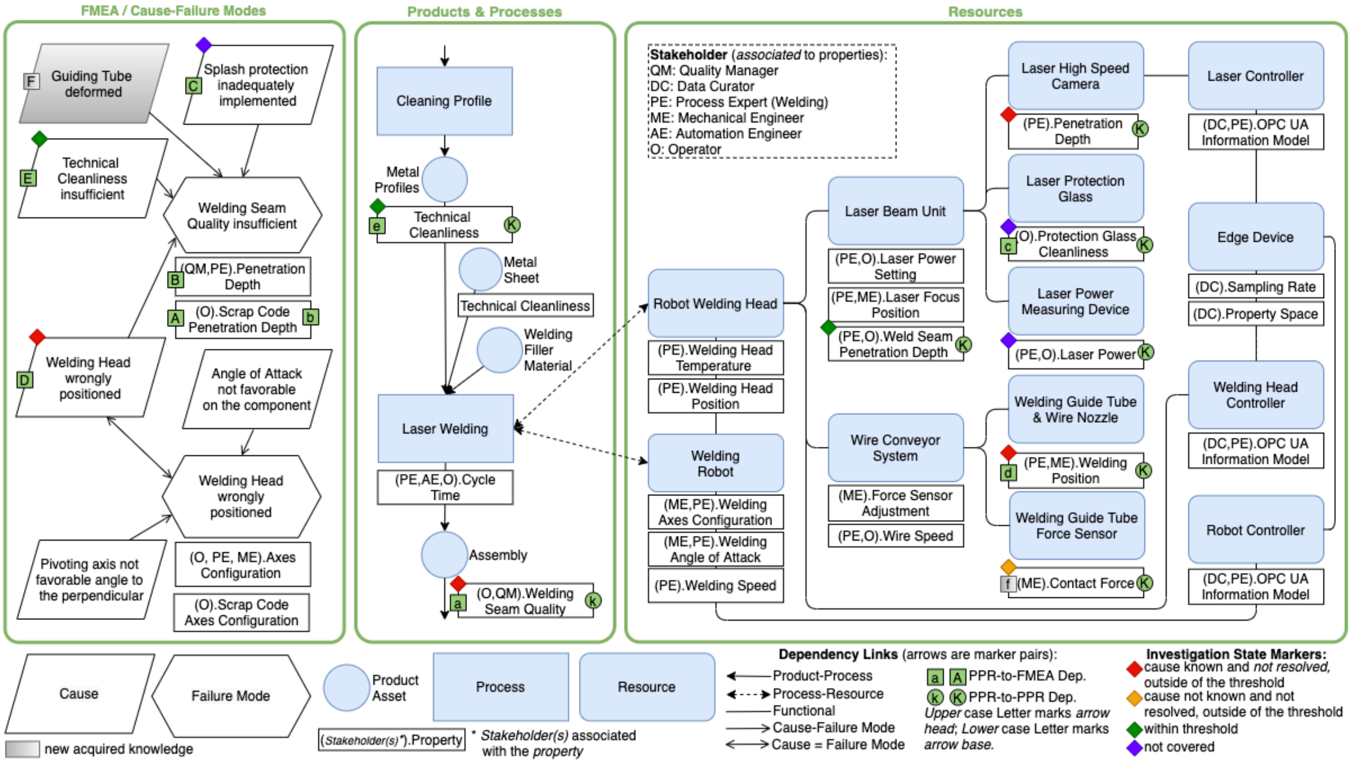

Fig. 2. *FMEA-linked-to-PPR Asset Issue Analysis (FPI) Model* for the use case *Weld Seam Quality*.

QM reacts to customer complaints and develops strategies to mitigate issues with specific target measures. The QM has a detailed overview on the products and production processes in the work scope and a rough idea about the mechanical production resources.

The *Process Expert (PE)* has specialized expertise in specific technologies, such as laser beam welding or milling. These experts have detailed information about causes and failure modes in their field and are, therefore, involved in the creation of the FMEA early. To identify complex relations, they possess detailed knowledge about the product and process, mechanical resources, and their configuration.

The *Mechanical Engineer (ME)* is, together with the process expert, responsible for the design of the machine and the development of production equipment, also supervising the production process. Mechanical engineers have abstract knowledge about the configuration possibilities of the production resources and an in-depth knowledge of the specific process steps and mechanical resources.

The *Data Curator (DC)* manages in the project the data integration of Product, Process, Resource (PPR) concepts and artefacts in a suitable data infrastructure. To integrate the data sources from the various domains, they need to have an abstract understanding of the PPR concepts they have to integrate. Furthermore, they mediate discussions between the data scientist and domain experts.

The *Operator (O)* monitors and configures the machine during production. Their main task is to ensure that the machine produces within the desired quality tolerances and has minimal breakdowns to maintain a high Overall Equipment Effectiveness (OEE) and they typically have detailed knowledge on efficient parameter settings to tune their machine for optimal performance. They have an abstract understanding of the FMEA concepts, but their domain knowledge of the process is usually limited to their specific work cell. This limited view makes it difficult for the operator to identify complex causes that concern previous or subsequent production steps.

As can be seen from these heterogeneous views, investigating quality issues in production typically requires a combination of different domain expert views. The *FMEA-linked-to-PPR Asset Issue Analysis Model* (cf. Section 4, FPI components and their interplay) has been designed to harmonize theses stakeholder views, facilitate their collaboration, and guide quality issue analyses.

4. FMEA+PPR ISSUE ANALYSIS (FPI) MODEL

The *FMEA-linked-to-PPR Asset Issue Analysis (FPI) Model* builds upon the ideas introduced in Kropatschek et al. (2021): to combine cause-effect relations derived from FMEA knowledge with PPR assets networks in a QDG. Rinker et al. (2021) built on the QDG by proposing the FMEA-linked-to-PPR assets (FMEA+PPR) meta-model to formally describe newly established links between FMEA concepts and PPR assets. The FPI Model provides a foundation for a guided issue analysis process (cf. Section 5). To facilitate this process, the FPI Model shall *(i)* represent the domain knowledge to systematically identify the most promising starting points for investigating quality issues and *(ii)* allow efficient cooperative analytic processes among domain experts to discover and verify the likely cause(s) for observed quality issues.

To resolve quality issues, it is common in the manufacturing domain to investigate the cause by applying an iterative trial-and-error approach. We mirror this concept, but aim to efficiently guide it to require fewer iterations in order to reduce costs and machine downtime.

For guiding issue analysis, Fig. 2 shows the FPI Model with its sub-models in the context of the use case *weld seam quality* (cf. Section 3): *(i)* The FMEA model captures failure modes and maps observed quality issues to FMEA concepts (green boundary box on the left). Concepts in causes, such as Welding Head or Penetration Depth, are linked to PPR asset properties to provide a meaningful context for the diagnosis, once a deviation is detected. *(ii)* The PPR model provides detailed insights about the assets, properties, technical and domain-specific dependencies (green boundary boxes in the center and on the right). *(iii)* The FMEA-linked-to-PPR assets (FMEA+PPR) model links PPR elements with quality issues in the FMEA.

To provide a detailed overview of the composition of the system for the stakeholders, the sub-models are linked with the following types of edges indicating their dependencies: Functional dependencies between resources are represented as undirected, solid edges; product-to-process dependencies are modelled by directed solid edges; dependencies between processes and resources are shown as bidirectional, dashed edges. PPR-to-PPR dependencies are shown as green circles containing a letter. Dependencies between PPR asset properties and the FMEA are linked by green squares containing a letter. The dependencies were identified as described in (Kropatschek et al., 2021).

A *failure mode* is a condition that triggers a quality issue in production and can be associated with multiple causes, illustrated by directed *cause-failure mode dependency* links. Each of these causes is necessarily a failure mode as well, but there can be failure modes that are not causes. If the failure mode is not a cause, it describes a potential state of the production system, hence it can be seen as an effect. This is highlighted by bidirectional *cause = failure mode dependency* links. Modeling the dependencies between assets, processes, causes, and failure modes (effects) is crucial to support quality issue analyses, as they enable the traversal of dependency pathways.

To track and guide the collaborative diagnostic process, the FPI approach uses *investigation state markers* that are placed on model elements to indicate their current coordination state. Specifically, there are four types of investigation state markers:

(i) A *red diamond marker* indicates an unresolved quality issue or (property) deviation. They are applied either to causes in the FMEA model or to FMEA elements that are known causes for a given quality issue. Red markers indicate issues such as property deviation that have not been resolved.

(ii) An *orange diamond marker* indicates a deviation (such as a threshold violation) or quality issue where the cause is presently unknown and therefore there is no *PPR-to-FMEA dependency* linked. If the cause can be identified by the stakeholder and is linked in the FPI Model, the color of the investigation state marker will change to red.

(iii) A *violet diamond marker* indicates hypothesized deviations that are currently not detectable or not covered by available data. This can have several reasons, such as undefined thresholds for detection or unavailable property data (e.g., no sensor exists that can provide measurements). Resolving issues marked with violet markers requires some form of intervention, e.g., manual checking by an operator or additional instrumentation. If the value of the property is determined during the intervention, the color of the marker will change accordingly. In case the property is within a normal range after the intervention, the marker will change to green. If a property deviation is discovered, the color will change to red or orange.

(iv) A *green diamond marker* indicates that a PPR element has been properly mapped to a cause in the FMEA model, and no property deviation has been detected. Hence, the green markers indicate that elements are relevant and linked to causes and failure mode properties, but are not (or no longer) the cause of a quality issue under investigation.

An investigation state marker is either *(i)* applied manually by a domain expert, *(ii)* generated through an automated process, e.g., an automated quality inspection system or a deviation detection module that detects threshold violations on individual parameters, or *(iii)* added through propagation. The propagation mechanism works as follows: *product asset quality issues* are linked with *PPR-to-PPR dependencies* with resource properties. Resource properties are linked to failure modes (properties) and causes through PPR-to-FMEA dependencies. By following these dependencies, the investigation state markers can be propagated through the graph. If all markers have been investigated (green) and quality issues still remain, further analysis can be conducted by following the bidirectional *cause = failure mode dependency* links. Newly introduced links to failure modes connected to other resources iteratively extend the analysis space with additional branches and trigger possible further investigation tasks, indicated by a yellow or red diamond marker.

5. FEASIBILITY STUDY

To validate the feasibility of the *FPI Model*, two authors of this paper conducted an initial feasibility study in a manufacturing environment similar to the use case *weld seam quality* (cf. Section 3). The feasibility study revealed that the resulting FPI knowledge graph can become highly complex and extensive. Therefore, we decided to support the stakeholders with two software modules for configuration and for deviation detection.

The *configuration module* supports the data curator in semi-automatically registering machine data properties on an edge device. To this end, we added *machine controller* and an *edge device* as resources to include machine and data interfaces and to link the FPI Model to machine run-time data. For machine controllers that expose sensor data via a OPC Unified Architecture (OPC UA) server and provide a standardized information model, properties can be queried semi-automatically. Typically, only a small fraction of these properties are relevant, modeled in the FPI, and recorded during production by the edge device. Others properties are typically only captured, integrated, and analyzed in the event of a quality issue.

The *deviation detection module* observes the machine data/properties stored on the edge device and triggers the analysis of the FPI Model in the event of a quality issue. In this use case, a scrap code, such as insufficient weld seam quality, classifies the the quality issue. The deviation detection determines if a property is outside of its normal range or if a threshold previously set by the data curator has been violated, in order to identify relevant causes from within the large graph. Based on the relevant properties and dependencies of these identified potential causes, stakeholders who are likely to be relevant to the issue can be notified.

To address the requirements for efficient quality issue analysis (cf. Sections 1 and 3), the authors built on the *FPI Model* to conduct the following *FPI Method* steps.

FPI Step 1. Identify and configure machine controllers, data interfaces and edge device. Result of this inventory step are selected properties, integrated into the FPI Model. The *data curator* registers, with the help of the *configuration module*, all available properties of the machine controller in the property space of the edge device, and – if possible – assigns the respective resources and stakeholders. Domain experts define thresholds and sampling rates for selected scenarios.

FPI Step 2. Assign investigation state markers. Result of this step are FPI elements annotated with investigation state markers (cf. Section 4 and Fig. 2). If a production step, such as *laser welding*, produces scrap, the operator or the quality manager assign a scrap code to the process asset (cf. Fig. 2). This scrap code will start the quality issue investigation with support of the deviation detection module, which links and processes current machine data and predefined thresholds with the FPI Model. The quality issue investigation is an iterative process. To collect the necessary information for the next iteration, it is often necessary to adjust data acquisition parameters, such as the sampling rates of properties by changing the configuration of the edge device. Investigation state markers provide valuable guidance for the selection of the properties which require adjusting data acquisition parameters.

FPI Step 3. Analyze investigation state markers. Result of this step are domain expert activities and updated markers. The focus of this step is to identify likely causes and hypotheses on potential measures to resolve the quality issue. The operator and process expert query the investigation states in the FPI Model and act accordingly.

3.1 Red marker. The operator inspects the marked asset, which represents a deviation mapped to a cause, follows the dependencies, identifies causes and potential resolution actions.

3.2 Orange marker. A process expert investigates the marked asset, which represents a deviation in the property that could not be mapped to a cause, to investigate components associated with the property in the PPR and to establish hypotheses about possible causes in the FMEA sub-model.

3.3 Violet marker. The operator reviews the marked asset, which represents hypothesized deviations that are currently not detectable or not covered by available data. Therefore, the operator may want to consult with the process expert to discover causes and change the investigation state to red or green. Further, new parameters from the property space on the edge device can help to explain and address the quality issue. The data curator may add data sources, e.g., sensors with a higher sampling rate, to collect the data required to explain the quality issue.

FPI Step 4. Cause verification. Result of this step are (mostly) green investigation state markers. The process expert or operator verifies checking all markers and setting appropriate resolution actions as a precondition to resume production. Troubleshooting a machine may require several iterations of FPI Steps 2 to 4.

FPI Step 5. Add new cause to the model. Results of this step are an updated FPI Model and, if necessary, an updated edge device configuration. The process expert informs the quality manager to add a newly discovered cause and dependency links to the FMEA and to the FPI Model. To accommodate additional data related to the new detected causes, the data curator adjusts the configuration of the edge device.

Validation scenario, A real-world scenario encountered during the validation phase highlights the benefits of the FPI method in this application context (cf. the *Products & Processes* boundary box in Fig. 2). Starting point of the scenario was a trigger indicating the welding seam quality of a specific product was outside the required quality range. This was represented in the FPI Model as a red marker on the product property *Welding Seam Quality*.

The deviation detection module verified the property *Technical Cleanliness* of the metal profiles ($k \rightarrow K, e \rightarrow E$) to be within the required quality range (indicated by a green marker).

Reflecting the complexity of the production environment, starting from the same trigger, another pathway was analyzed. Based on the model dependencies between the *Welding Seam Quality* and other asset properties, the deviation detection module focused on checking the properties linked by green circles containing the letter K.

Here, a deviation detection module detected and marked two deviations: One in the property *welding position* of the wire nozzle attached to the *welding guide tube wire nozzle*, and one in the property *contact force* of the *welding guide tube force sensor*.

The property *welding position* was linked to the cause *welding head wrongly positioned*, shown by the relations containing the letter $d \rightarrow D$ and a red marker. This indicates that the deviation is properly mapped to a cause in the FMEA.

The orange marker at the resource property *welding guide tube force sensor* indicates that a deviation was detected, but that the property has not yet been connected to a cause in the FMEA. Welding process experts and mechanical experts came together to analyze the issue. The analysis of the value of the property *contact force* identified a new dependency between the *force/linear sensor*, the *penetration depth* and the deformation of the *guiding wire tube*, ultimately leading to a misalignment that negatively affected *weld seam quality*.

According to this causal chain, the quality manager can add the cause and the *Cause-Failure Mode Dependency* link ($f \rightarrow F$) to the FPI Model (highlighted in gray in Fig. 2). From then on, issues related to the added dependencies can be tracked automatically.

Discussion. Regarding our research questions, we found the FPI approach to enable the *quality manager* and *domain experts* to efficiently collect and disseminate cross-domain knowledge and made it easier to rapidly analyze quality issues. Furthermore, the feasibility study revealed the ability of the FPI approach to quickly identify likely causes for quality issues. This capability is especially helpful in production settings where even slight quality defects can be costly in terms of financial penalties or production delays.

Limitations of the initial feasibility study, such as limited scope and researcher bias, require the validation of the FPI approach with empirical studies in a wider range of application contexts.

6. CONCLUSION AND FUTURE WORK

The results of the feasibility study indicate the FMEA-linked-to-PPR Asset Issue Analysis (FPI) approach to satisfy the quality issue analysis requirements and to facilitate efficiently guided cross-domain collaborative issue analysis among stakeholders. Further, the study found the FPI approach to facilitate navigating complex causal relationships and systematically developing new hypotheses to explain quality issues, by referring to the multi-view coordination assets in the FPI Model.

A current limitation of the FPI approach is delayed detection, i.e., once a quality issue is detected, it is typically too late to prevent scrap in production. An important direction for future research is therefore the integration of monitoring mechanisms that can immediately start quality issue analysis and trigger resolution actions in case of recognized deviations or risky trends in measured data. Hence, future work will aim at recording and integrating feedback from the application of the FPI approach, e.g. for the prioritization of potential causes, investigation state markers, and resolution actions for risk mitigation.

Furthermore, we will extend the application of the FPI Model to a larger scope in production, e.g., a work line, which will require the integration with issue tracking systems. Finally, future work will focus on supporting data-driven exploration for cause analyses. To this end, we plan to develop methods for monitoring and analyzing the vast space of machine parameters for deviations that may help to identify causes of quality issues.

In the long term, we aim to develop the FPI Model into a foundation for systematic multi-view data management in data-rich digital manufacturing systems, where capturing and analyzing all potentially available data is typically infeasible and therefore requires knowledge-based guidance and prioritization.

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