Designing a Digital Shadow for Efficient, Low-Delay Analysis of Production Quality Risk

Sebastian Kropatschek* Oskar Gert* Iman Ayatollahi* Kristof Meixner†‡
Elmar Kiesling** Alexander Steigberger[xi] Arndt Lüder*[x] Stefan Biffl*†
*Center for Digital Production, †Inst. of Information Sys. Eng. TU Wien, ‡Christian Doppler Lab. SQI, Austria
E-Mail: [first].[last]@tuwien.ac.at
**Institute of Data, Process, and Knowledge Engineering, WU Wien, Vienna, Austria
E-Mail: elmar.kiesling@wu.ac.at
[x]Institute of Ergonomics, Manufacturing Sys. and Automation, Otto-von-Guericke U., Germany
E-Mail: arndt.lueder@ovgu.de
[xi]Neuman Aluminium, CAG Holding GmbH, Austria

***Abstract*—Manufacturers in the automotive industry extensively rely on iterative process Failure Mode and Effects Analysis (FMEA) in their quality management. Process FMEAs model technical impacts based on engineering artifacts. However, traditional process FMEA methods are typically document-centric and do not integrate feedback from the shop floor without significant delay. In this paper, we introduce the *Digital Shadow for Production Quality Analysis (DS-PQA)* method and system design that integrates feedback from machine components on the shop floor. To this end, the method leverages FMEA and production system engineering models to configure OPC Unified Architecture (OPC UA)-based data acquisition. Based on that data acquisition, the DS-PQA system analyzes data from the shop floor to (i) inform operators on likely causes of a production defect, and (ii) alert FMEA experts about FMEA causes that occur more frequently than expected and should be re-validated. In a feasibility study, we evaluated the effectiveness and efficiency of the DS-PQA method and system on a welding cell that manufactures automotive parts. The study results indicate that the DS-PQA method and system are feasible, more efficient, and can substantially lower the latency for analyzing production quality risk compared to a traditional approach.**

***Index Terms*—Production Systems Engineering, Industry 4.0 component, process FMEA, PPR, Digitalization.**

I. Introduction

In automotive manufacturing, iterative process Failure Mode and Effects Analysis (FMEAs) can help engineers, operators, and maintainers to improve the production system and its processes by informing them about likely causes of production quality issues [1]. FMEAs describe failure modes, their likely causes, and countermeasures and aim to analyze and mitigate risks. The authoring of such FMEAs typically requires modeling technical impacts based on engineering models and interpreting results from quality lab tests [2]. Synchronizing the FMEA with modifications on the shop floor to reflect insights from the real production environment accurately requires frequent adaptations [3], [4] and careful management [5]. However, this process is typically time-consuming and, hence, conducted infrequently. Therefore, integrating insights that emerge from ramp-up and operation due to the reconfiguration and adaptation of resources on the shop floor is a challenge [5]. Maintaining alignment between FMEAs and production reality is challenging and requires adaptation of FMEA aspects, such as the likelihood of particular causes for a production issue (e.g., inaccurate welding on a specific machine). This task is difficult, because process FMEA experts often do not receive timely feedback data from the shop floor [1].

DOI:

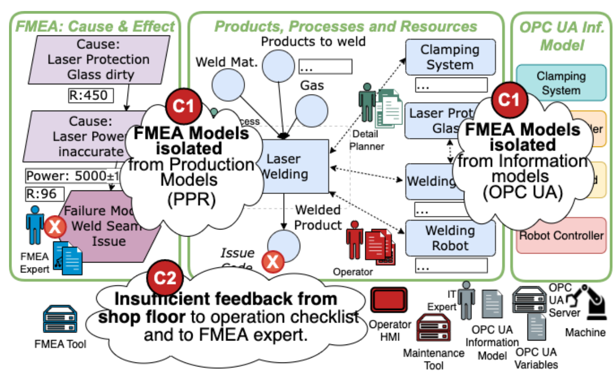

Fig. 1. Research challenges (DIN 60812 [6], VDI 3682 [7], OPC UA [8]).

Fig. 1 illustrates two major research challenges for FMEA experts, detail engineers, and plant operators. The engineers have different, partial knowledge of the production system that is required to identify, prioritize, and address causes of effects that may impact production quality [5]. With an operation checklist, i.e., a list of causes related to maintenance operations, the machine operator can follow a structured process to solve a quality problem classified by an issue code.

C1. Insufficient feedback from the shop floor to the (i) operation checklist and (ii) FMEA expert. On the one hand, the operator requires guidance on probable causes of production issues to address them quickly and correctly. However, the likely causes for a particular production defect are often difficult to determine accurately. The FMEA expert, on the other hand, needs accurate estimates for the probability of causes of production issues. Based on that, the expert needs to become aware of anomalies – i.e., if a cause is detected significantly more often than expected. However, the FMEA expert often receives incomplete or late feedback and data from the shop floor. Further, the transfer of implicit operator knowledge to the FMEA expert is also difficult, making it hard to reuse and improve the risk analysis. This difficult knowledge transfer and integration is mainly due to the limited alignment of the knowledge spaces of FMEA experts and operators [5].

C2. FMEA models isolated from production models. Although various models for FMEA [6], [9], multi-disciplinary production systems engineering (Product-Process-Resource (PPR)) [7], [10], and machine data (OPC Unified Architecture (OPC UA)) [8] exist, these models are typically isolated. To resolve a given production issue, operators and FMEA experts need timely feedback on the prioritization of measures, which requires an integration of these models.

In this paper, we tackle these challenges by integrating FMEA knowledge with engineering and production resource information models and introducing a system that (i) guides an operator in analyzing and resolving production issues, and (ii) informs an FMEA expert of the need to re-validate the FMEA w.r.t. a cause of a production issue. To achieve the former, the system generates operation checklists that prioritize FMEA causes based on their likelihood derived from machine data correlated to the issue. For the latter, it detects anomalies for particular machines (e.g., overheating of a welding head) if FMEA cause conditions evaluate to true more often than expected for a given time interval.

The remainder of this paper is structured as follows. Section II summarizes related work on FMEA, knowledge management in production systems engineering, and data collection from the shop floor. Section III motivates the research question and approach. Section IV introduces the illustrative use case *laser welding issues with feedback from the shop floor*. Section V outlines the *Digital Shadow for Production Quality Analysis (DS-PQA)* method and system for improving FMEA with knowledge from the shop floor. Section VI reports and discusses results from a feasibility study that applies the DS-PQA approach with real-world industry data. Section VII concludes and delineates future work.

II. Related Work

This section summarizes related work on FMEA, on knowledge management in production systems engineering, and on data collection from the shop floor.

FMEA approaches. FMEA is a mature methodology applied in various fields – Sharma *et al.* [2] provide an overview on the development of FMEA methods in general, whereas Wu *et al.* [11] focus on the use of FMEA models in manufacturing. To integrate engineering knowledge in the creation and use of FMEA models, Huang *et al.* [9] propose to combine FMEAs with model-based engineering. Such integration can be challenging, but the benefits – e.g., in terms of making it possible to derive rule-based information sets to guide ramp-up processes – are significant [1].

In this paper, we focus on FMEA approaches that provide actionable guidelines for data collection from the shop floor. In this category, various problem solving-oriented and increasingly data-driven FMEA models have been developed to support, i.a., maintenance [12], fault detection, diagnosis, and problem solving [1], [13]. These lines of research have shifted the focus of FMEA from preventing quality issues at the process design stage towards integrating FMEA models into highly dynamic and flexible I4.0 environments. To this end, Arévalo *et al.* [1] developed an extended FMEA (eFMEA) and linked it to an OPC UA information model that enables the triggering of failure modes based on OPC UA value readings. The research also resulted in an interface for communication of the causes of the failure mode as well as the steps to solve the problem for the operator. The focus in that work is on resource risks and extend process FMEA in tabular format to define and monitor system component variables in comparison to thresholds that define FMEA causes.

Knowledge management in production systems engineering. Production system engineering is a multi-disciplinary and multi-model process where different engineering disciplines develop the necessary documents to physically set and ramp up a production system [14]. Increasing digitalization of all production system life cycle phases has resulted in engineering domain models that aid shop-floor operators in managing the ramp-up progress [5]. Dombrowski *et al.* [15] indicate how concepts of Industry 4.0 – in particular a network of Industry 4.0 asset administration shells – can help to manage the complexity of change, in particular for production ramp-up.

Results of the production system engineering phase cover the production resources and their relations to the production processes to automate as well as the involved materials and products. This Product-Process-Resource (PPR) orientation [16] is traditionally covered by separate models. Recent research has shown that an integrated model of all assets within a production system, such as a PPR Asset Network (PAN) [10], can be beneficial. It provides a foundation for integrated risk analysis [17]. In this paper, we build on and integrate FMEA [9], a PANs [10], and OPC UA [8] models to collect shop floor data for efficient analysis of production quality risks.

Kropatschek *et al.* [18] identified the need to represent cross-domain quality knowledge for efficient data analytics. Based on that, they [17] introduced the *FMEA-linked-to-PPR Asset Issue Analysis (FPI)* approach that links a process FMEA model to a PPR Asset Network; this provides a foundation for systematically exploring causes of product and process quality issues associated with resources that automate a production process, such as laser welding of car parts. This paper builds on the FPI approach to investigate how to tune process FMEA risk ratings with feedback from production.

Data collection from the shop floor. Extensive research has addressed the acquisition and systematic collection of data from the shop floor as well as on how to relate such data to a digital representation of the production system, i.e., as a Digital Twin (DT). Kritzinger *et al.* [19] proposed a DT typology consisting of (i) Data Models (DM), defined as a digital representation of the physical model with manual data exchange between the digital and physical systems; (ii) Shadow Models (SM), where the data exchange is automatic from physical to digital, but manual from digital to physical; (iii) and Digital Twins (DTs) with automated exchange in both directions. In this paper, we design a digital shadow.

OPC UA is an industrial communication standard [8] that allows information to be exposed (browse, read, subscribe to, ...) following the client-server model. The OPC UA Base specifications offer a rich set of information model elements. Companion specifications offer standardized information models for specific use cases or equipment types. As an example, the companion specification *OPC UA for Machine Tools* offers standardized information models for CNC machining [20]. Vendors of industrial equipment can implement standardized OPC UA companion specifications on controls of their machines in order to facilitate interoperability between machine controllers and other IT-equipment at customers' shop floors.

In this paper, we go beyond the state of the art by connecting production issues to root causes in resources, by rating FMEA causes bases on shop floor data, by considering the history of FMEA cause presence, and by facilitating a backflow of information from the shop floor to re-validate FMEA causes.

III. Research Question and Approach

Our main research goal is to efficiently collect and contextualize shop floor data in order to rate causes of production quality risks. To this end, a key research goal is to integrate FMEA modeling with multi-disciplinary engineering models. To tackle this research goal, we followed the *Design Science* approach [21].

First, the authors reviewed literature on FMEA in production quality applications [11]. Next, four authors conducted stakeholder focus workshops with seven FMEA and engineering experts at three large European system integration companies in automotive manufacturing. The workshops focused on product quality issues with robot cells for joining car parts [22]. In particular, the workshops focused on (i) required multi-disciplinary knowledge for risk analysis, (ii) their approaches to risk analysis and FMEA modeling, (iii) gaps in the integration of multi-disciplinary knowledge and data collection from the shop floor, and (iv) requirements for knowledge integration, validation, and analysis to identify and rank root causes of production quality issues. From the domain analysis, we abstracted the use case use case *laser welding issues with feedback from the shop floor* (cf. Section IV) and derived the following research question (RQ).

RQ. *What model-driven approach can leverage FMEA and engineering models to analyze production quality issues efficiently and with low latency based on data from the manufacturing shop floor?* To address this RQ, we designed and evaluated the Digital Shadow for Production Quality Analysis (DS-PQA) approach that consists of (i) the *DS-PQA method* and (ii) the *DS-PQA system* with the following requirements.

The DS-PQA method builds on the FPI method [17] that integrates FMEA and PPR modeling. The DS-PQA method shall (i) enrich an initial PPR model from an OPC UA information model, (ii) link similar domain concepts in the FMEA, PPR, and OPC UA models, (iii) configure the DS-PQA system for data acquisition from the shop floor, and (iv) configure the DS-PQA system to analyze the acquired data in order to provide prioritized lists of likely causes for given issues as well as to detect anomalies that necessitate an FMEA re-validation.

The DS-PQA system design shall describe the technical solution elements to automate steps of the DS-PQA method, in particular, data collection and analysis from the shop floor.

IV. Use case Laser Welding

This section introduces the use case *laser welding issues with feedback from the shop floor*. We abstracted the use case from a domain analysis focused on linking feedback from the shop floor to FMEA models. Specifically, the use case is focused on product quality issues with robot cells for joining car parts in automotive production at a large system integration company [17]. This domain analysis provided a setting for evaluating the design of a digital shadow for low-latency analysis of production risks.

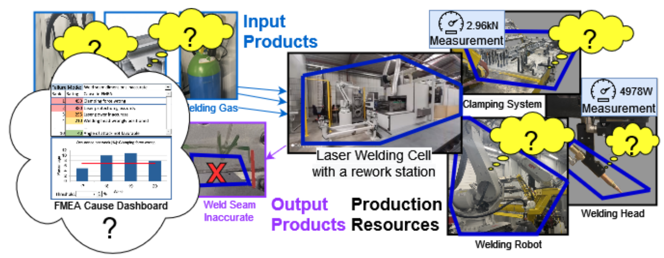

Fig. 2. Production quality issues, resources, and data in *Laser Welding*.

Production quality issues in laser welding. Fig. 2 provides an overview on a laser welding cell that joins aluminum parts in two welding steps. The cell consists of two clamping robots, a robot for moving the parts within the process, and two welding robots with high-speed cameras for online welding seam inspection. If quality inspection detects a weld seam that does not meet quality requirements, it assigns an issue code and transfers the part to a manual rework station. Each issue code maps to one or more failure modes that each typically are associated with up to 20 causes in the FMEA. At the rework station, the operator can see an operation checklist of potential solutions to address the issue code.

FMEA feedback from the shop floor. A common goal of the stakeholders is to provide the operator with the current best knowledge on solutions to a production issue. In this context, the FMEA reflects the current state of the working hypotheses of the FMEA and engineering experts on causes of a production issue and the impact of solutions on operations.

The operation checklist, which ranks causes based on the risk priority number (RPN) of its associated FMEA cause, should guide the operator in efficiently and quickly addressing an issue code. To this end, the operator may have to investigate several candidate causes, possibly finding new solutions for a problem. Identified solutions as well as update suggestions for RPNs are currently communicated and discussed between operators and the FMEA expert with significant delay – typically in weekly meetings. Therefore, significant operator knowledge is likely not to be reported to the FMEA expert.

Operation IT collects machine data, using an OPC UA information model that reflects the resource structure. A data collection system correlates the machine data with production steps and work pieces, stores the data for analysis, and provides visualizations in custom dashboards. However, there is no direct feedback path from issue causes and associated machine data to the FMEA expert.

Traditional approach to FMEA re-validation. In the domain analysis, we found that traditional FMEA approaches for product quality management focused on detailed modeling of causes to identify appropriate countermeasures in product engineering phases. Leveraging and validating FMEA knowledge during ramp-up and production, by contrast, was not well supported. This is also evident in the fact that modeling means available in modern FMEA tools, such as APIS[1], are limited to modeling FMEA trees, rather than graphs that relate to engineering knowledge.

The resulting FMEA models were therefore only implicitly related to engineering knowledge and OPC UA information models, making it difficult to connect FMEA concerns to production system reality. Therefore, changes to resources often relied on invalid assumptions regarding FMEA causes that were not grounded in production reality. Consequently, this required a re-validation of the FMEA, which contained hundreds of cause-effect relationships.

To improve the method to efficiently identify FMEA causes for re-validation and improve integration of engineering knowledge on production resources, the FMEA experts proposed a low-latency feedback cycle to analyze production data considering (i) machine data correlated to FMEA cause likelihood; and (ii) changes to the production system to keep the FMEA model consistent with the production models.

V. Solution Approach

This section introduces the DS-PQA method and system illustrated in Fig. 3. The upper half of the figure shows the *Digital Shadow model* that consists of linked FMEA, PPR, and OPC UA models. These models represent the knowledge required for conducting the DS-PQA method. The lower half of Fig. 3 illustrates the DS-PQA method steps (large arrows) of linking and validating the models, configuring the DS-PQA system for machine data collection and analysis, and analyzing the machine data with FMEA causes to inform operation checklist prioritization and FMEA cause re-validation (cf. the cause marked with a red diamond). Furthermore, the lower part of the figure also shows the technical elements to operate the DS-PQA system (green box at the bottom), in particular tools for model design and linking, for machine data collection, and for data analysis.

[1]APIS FMEA Tool: https://www.apis-iq.com/software/

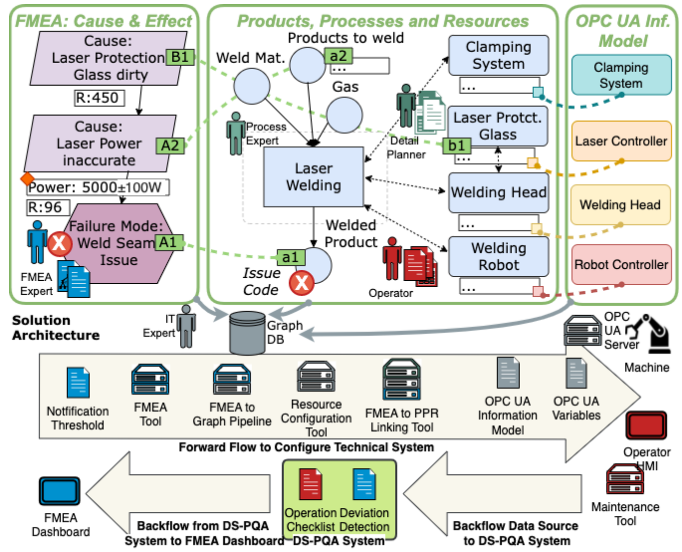

Fig. 3. *Digital Shadow for Production Quality Analysis*: Solution Overview.

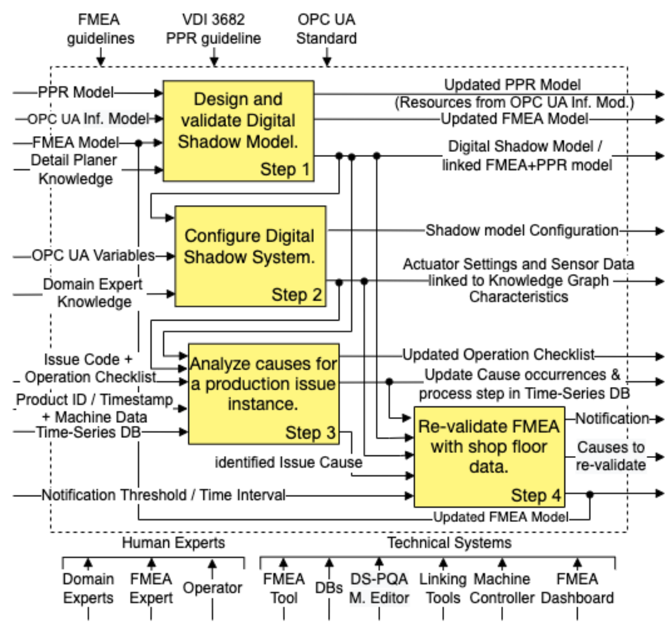

Fig. 4. DS-PQA Method (in IDEF0 notation [23]).

DS-PQA Method. To integrate and validate the FMEA with the PPR and OPC UA knowledge required to analyze FMEA causes with feedback from the shop floor, we propose the DS-PQA method (cf. Fig. 4) that – over a set of failure modes – results in (i) updated operation checklist priorities and (ii) FMEA causes that are marked for re-validation. Domain experts conduct the method in their FMEA and engineering environments, supported by an FMEA tool, a DS-PQA model editor, and a graph database. It consists of four steps that can be performed iteratively to consider new knowledge in the goals or use case environment.

Step 1. Design and validate Digital Shadow Model. In this step, the FMEA expert collaborates with the detail planner to refine the PPR model and link domain concepts in FMEA causes – in particular, in logical conditions that specify the FMEA cause – to PPR and OPC UA elements. Next, they validate the completeness and correctness of the links. The FMEA expert sets initial RPN values based on experience from historic production cell designs. Together with the process expert, the FMEA expert specifies thresholds (*min*, *max*, *range* etc.) for the characteristics of failure modes and causes.

Inputs to this step are (i) an FMEA model with implicit reference to resources; (ii) a PPR model; (iii) an OPC UA Information model; and (iv) detail planner knowledge on necessary production resource design details.

Results of this step are (i) updated FMEA and PPR models; and (ii) the digital shadow model, i.e., a FMEA-linked-to-PPR assets (FMEA+PPR) model.

Step 2. Configure DS-PQA System. In this step, the IT expert selects OPC UA variables that correspond to the specified characteristics and configures the OPC UA subscriptions and thresholds.

Inputs to this step are (i) the digital shadow model, i.e., a FMEA+PPR model; (ii) machine data in OPC UA variables; and (iii) domain expert knowledge required for configuration.

Results of this step are (i) DS-PQA system configuration according to the digital shadow model; and (ii) links between the digital shadow model and OPC UA actuator setting and sensor data.

Step 3. Analyze causes for a production issue instance. This step is triggered by an issue code event that causes the DS-PQA system to analyze the issue. In particular, it evaluates which logical conditions associated with FMEA causes evaluate to true, based on the machine data related to the process step that generated the issue code. This analysis with current machine data is used in the generation of an operation checklist with likely causes for a production issue. Algorithm 1 specifies the ranking of FMEA causes in the operation checklist.

The goal of the algorithm is to prioritize the input operation list and return ranked (descending by RPN) lists of high, medium, and low priority operations: (i) *High*: causes with measured characteristic values outside of the normal range; (ii) *Medium*: causes where associated characteristics cannot be measured automatically; (iii) *Low*: causes with measured characteristic values within the normal range. The *evaluate* function checks whether any condition for a cause is fulfilled and returns true in case of a threshold violation.

Inputs to this step are (i) the digital shadow model; (ii) the operation checklist for an issue code; (iii) a product id, production timestamp and machine data; and (iv) and a time-series database that stores causes with conditions that evaluated to true. The step results in an updated operation checklist.

Step 4. Re-validate FMEA with shop floor data. In this step, the quality engineer specifies for each FMEA cause a notification threshold based on Key Performance Indicators (KPIs) (i.e., number of identified causes per total number of produced parts) concerning a specific time interval (e.g., one week). The DS-PQA system then checks whether a FMEA cause exceeded this threshold in the most recent time interval (cf. Algorithm 2). The *count_occurred* function returns the number of threshold violations associated with a cause CO that resulted in Not OK parts during a given time interval t. The algorithm returns a set of causes that occur more often than expected; the system marks those for re-validation and notifies the FMEA expert.

Algorithm 1: Rank causes in operation checklist.

Input: An initial set of operations $IO = \{IO_1, .., IO_n\} \;\forall\; IO_x \;\exists$ a cause CA with a RPN and a set of logical conditions $C = \{C_1, .., C_n\}$

Output: Three lists of newly ranked operations $high, medium, low$ ordered by RPN

$high = \emptyset, medium = \emptyset, low = \emptyset$;
while $IO \neq \emptyset$ **do**
  $pop(IO_x)$, $CA_{current} = IO_x(CA)$, $C_{current} = CA_{current}(C)$;
  if $C_{current} = \emptyset$ **then**
    $medium := medium \cup IO_i$;
  end
  while $C_{current} \neq \emptyset$ **do**
    $pop(C_i)$, $t = evaluate(C_i)$;
    if $t == true$ **then**
      $low := low \cup IO_i$;
    else
      $high := high \cup IO_i, break$;
    end
  end
end
$sort(high, RPN), sort(medium, RPN), sort(low, RPN)$;
return $high, medium, low$

Algorithm 2: Select FMEA causes for re-validation.

Input: A set of causes $C = \{C_1, .., C_n\} \;\forall\; C_x \;\exists$ a category Id and a threshold T; a time interval t; a set of time-stamped occurred causes $CO = \{CO_1, .., CO_n\}$

Output: A set of causes for re-validation CV

$CV = \emptyset$;
while $C \neq \emptyset$ **do**
  $pop(C)$;
  $occurrence = count\_occurred(CO, C(Id), t)$, $allowed_{occurence} = count\_allowed(C(T), t)$;
  if $occurrence > allowed_{occurence}$ **then**
    $CV := CV \cup C$
  end
end
return CV

Inputs to this step are (i) the digital shadow model; (ii) time-series machine data for the specified time interval ; (iii) a notification threshold that determines how many times a cause can occur before the responsible stakeholder is notified.

Results of this step are (i) a notification to the quality engineer; and (ii) an FMEA model updated with re-validation marks.

DS-PQA system. The DS-PQA system includes the following technical solution elements (cf. Fig. 3) that automate steps of the DS-PQA method – in particular, collection and analysis of data from the shop floor.

In Step 1, the *FMEA to PPR linking tool* facilitates defining dependency links between FMEA, PPR, and OPC UA model elements (cf. Fig. 3, green markers linked with dashed lines).

The *FMEA+PPR to graph transformation pipeline*, implemented in Python[2], (i) parses and transforms XML data from the *FMEA tool*, and (ii) inserts the parsed data into a Neo4j[3] graph database. Thereby, it creates and stores the digital shadow model as a knowledge graph.

In Step 1 and 2, the *resource configuration module* partially automates the data collection and the configuration of PPR resources.

In Steps 3 and 4, the *DS-PQA system* collects characteristic data from *machine controllers* exposed by an OPC UA server and from *Maintenance Tools*, such as *Ispro*[4], which provide time-stamped machine service events. For a production issue, the DS-PQA system receives an operation checklist with causes and associated logical conditions. These conditions refer to characteristics linked to *OPC UA* subscription values and typically define a valid range for this value. A core component in the DS-PQA system is the *deviation detection model*, which uses the *math expression plugin*[5] to evaluate logical conditions regarding machine data. Finally, the *FMEA expert dashboard* (cf. Fig. 6) displays analysis results, such as statistics on how often characteristics violate their valid range, and FMEA causes that require re-validation.

VI. Results and Discussion

This section reports on and discusses results from employing the DS-PQA approach in the use case context. In a feasibility study, we evaluated the effectiveness, efficiency, and timeliness of notifications generated by the DS-PQA approach. To this end, three FMEA and domain experts – guided by three authors of this paper – applied the DS-PQA method in a real-world production scenario. This involved (i) designing digital shadow models for failure modes such as *Weld Seam Dimensions inaccurate* (cf. Fig. 5); (ii) analyzing the effort required to apply the DS-PQA method; and (iii) collecting data on the issue resolution latency of the DS-PQA approach in comparison to the traditional approach – i.e., FMEA without feedback from the shop floor.

Digital Shadow Model. Fig. 5 shows a Digital Shadow model with its sub-models for the production quality issue *Weld Seam Dimensions inaccurate*. *(i)* The FMEA model (two left-most model areas) consists of a tree of failure modes and causes with FMEA characteristics (e.g., *FMEA Profile Thickness not OK*), which link to PPR characteristics (e.g. *PPR Metal Profile Thickness* – cf. the green tags *A2* and *a2*). *(ii)* The PPR model (three model areas in the center) details product assets, resource characteristics, and technical and domain-specific dependencies, forming a PAN knowledge graph [10] that connects product and process quality to resources that automate production. *(iii)* The PPR characteristics (e.g., *Clamping Force)* are tagged with squares in the color of the associated OPC UA Information Model (right-most model area) that is exposed by a OPC UA Server on a specific resource controller (e.g., the Clamping System Controller)

Together, these models form a knowledge graph that facilitates mapping production quality aspects to resource characteristics, in order to identify relevant data elements for machine data collection and analysis.

Conducting the DS-PQA method. *Step 1. Design and validate Digital Shadow Model.* In this step, quality engineers enhanced and validated a historic FMEA model in the *FMEA tool APIS*[1]. The model contained production system resources that could serve as a starting point for the PPR model. The *FMEA+PPR to graph transformation pipeline* converted the FMEA XML from APIS into a Neo4J graph. The FMEA expert mapped the OPC UA information models from four servers (Clamping System, Laser Controller, Welding Head Controller, Robot Controller) to the corresponding PPR model resources in the Neo4J graph, using a custom *resource configuration tool*. The FMEA and domain experts linked the FMEA and PPR model elements (e.g., the failure mode *Laser Power inaccurate* linked to *actual Laser Power*), using the *FMEA-to-PPR linking tool*. This step took approximately 40 person hours for the FMEA expert and two domain experts with a process facilitator.

Step 2. Configure DS-PQA System. IT experts and a detail planner configured the OPC UA variables for data collection on the *Fledge Platform*[6] on an edge device for storage in an InfluxDB[7]. A reference to the values of the variables is linked to the DS-PQA Model in a Neo4J graph database.

The configuration enables collecting and correlating selected data from the shop floor to production process steps and to production quality issues. This semi-automatic step took 10 person hours.

Step 3. Analyze causes for a production issue instance. When a production issue occurs, the DS-PQA system receives collected and correlated shop floor data on the issue, provided by a quality inspection system that uses a High Speed Camera[8] to identify inaccurate weld seam dimensions and trigger an issue code (cf. PPR dependency link in Fig. 5, small blue ellipses *r1* and *R1*). For risk analysis, the deviation detection module in the DS-PQA system identified the FMEA causes

[2]Python: https://www.python.org

[3]Neo4j: https://neo4j.com

[4]Ispro: https://www.ispro-ng.com

[5]C++ Mathematical Expression Toolkit Library (ExprTk)

[6]Linux Foundation Edge (FLEDGE) Architecture: https://www.lfedge.org

[7]InfluxDB: open-source time series database: https://www.influxdata.com

[8]http://www.lessmueller.de/en/products/weldeye

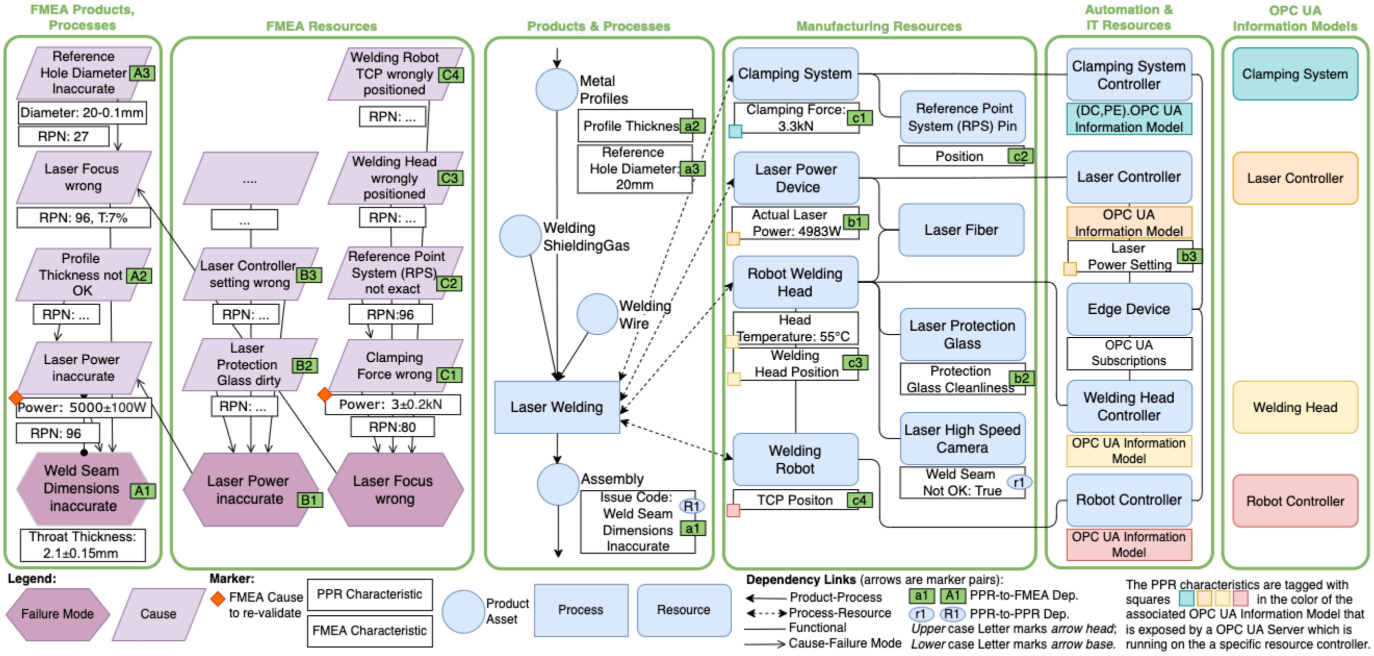

Fig. 5. Digital shadow model for issue *Weld Seam inaccurate* - FMEA rating [6] informed by backflow from shop floor, using VDI 3682 [7], and OPC UA [8].

associated to the quality issue and evaluated the logical conditions of these FMEA causes according to Algorithm 1. Furthermore, it used the acquired shop floor data to rank causes in the operation checklist. For example, a measured *clamping force* of 3.3 kN exceeded the target range 2.8 kN to 3.2 kN, leading to a higher ranking of the associated cause *Clamping Force* in the operation checklist (cf. Fig. 6, left-hand side). This step resulted in a prioritized operation checklist that FMEA experts and operators found useful and usable for selected test cases. This analysis step was automated and required no human effort.

Step 4. Re-validate FMEA with shop floor data. When a production issue occurs, the DS-PQA system analyzes the cause occurrence data in the time-series database. For example, the cause *Clamping Force wrong* occurred more often per week than the threshold of 7% of products per week. Therefore, the DS-PQA system marked the FMEA cause in the digital shadow model (cf. Fig. 5, FMEA cause marked with a red diamond) to notify the FMEA expert. This step resulted in an FMEA dashboard (cf. Fig. 6, right-hand side) that FMEA experts found useful and usable for selected test cases to analyze in detail the aggregated shop floor data for a marked cause and possibly to adapt the FMEA cause likelihood and/or to consider countermeasures. This analysis step was automated and took no human effort.

Addressing our research question, the model-driven DS-PQA approach leverages FMEA and engineering models to analyze production quality issues based on data from the manufacturing shop floor. Applying the DS-PQA approach was effective in deriving useful analysis artifacts, i.e., the improved operation checklist and the FMEA dashboard, fulfilling the

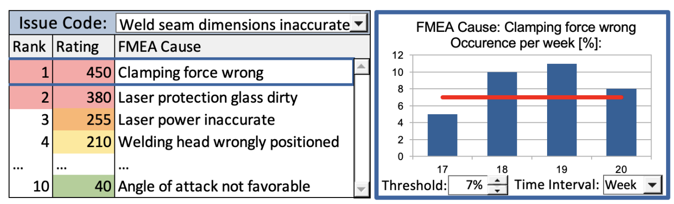

Fig. 6. Operation checklist for an issue and FMEA dashboard for a cause.

requirements for the DS-PQA method and system.

In the feasibility study, the DS-PQA approach was efficient, as (i) the human expert effort for modeling and configuring the DS-PQA system was reasonable for selected test cases and is expected to decrease further when reusing a digital shadow model and the associated OPC UA configurations for similar machines or processes in a work line; (ii) the operational risk analysis has been automated; and (iii) the results helped to focus the effort of the operator and the FMEA expert on the re-validation of the most relevant FMEA causes.

Furthermore, the DS-PQA approach has low latency in comparison to the traditional approach in the study context (cf. Section IV) as (i) the automated operational risk analysis takes seconds to minutes to achieve analysis results that before took weeks of expert work; (ii) the focus of the operator on the most relevant and likely FMEA causes on average reduces delay in production; and (iii) the focus of FMEA re-validation on the most relevant FMEA causes reduces the delay of adapting assumptions on cause that deviated from shop floor reality, e.g., after changes in the production ramp-up phase [5], from days or weeks to hours.

VII. Conclusion and Future Work

To support FMEA experts and operators with advanced analyses based on machine data from the shopfloor, this paper introduced the *Digital Shadow for Production Quality Analysis (DS-PQA)* method and system, which together provide a model-driven approach to designing a digital shadow for efficient and low-latency analysis of production quality issues for joining robot cells in manufacturing.

In an initial feasibility study, domain experts conducted the DS-PQA method, guided by authors of this paper, on a real-world robot cell for welding car parts. In this context, the study showed that the DS-PQA approach was (i) feasible in that the digital shadow provides the FMEA knowledge necessary to improve FMEA cause analysis, both for an operation checklist and for FMEA re-validation (cf. Fig. 6); (ii) effective in that the DS-PQA method resulted in digital shadows and analysis results, which experts on FMEA, laser technology, and operation found useful and usable; (iii) efficient as the domain experts found the DS-PQA method to focus on the most relevant FMEA causes to investigate for a production quality issue during operation and for FMEA re-validation; and (iv) low-delay as the automated collection and analysis of data from the shop floor could be used to inform operators and FMEA experts in minutes, compared to the traditional approach that took several days and did not connect FMEA causes to shop floor data. Although the DS-PQA method requires advanced maturity in terms of digitalization [15], these promising results warrant further empirical studies in a variety of application contexts. The results of this research also provide an incentive to consumers and producers of OPC UA information models to aim at designing sufficiently complete OPC UA information models[9].

Limitations. A key idea, but also inherent limitation of the approach is that it will only include data in likelihood assessments that are mapped to the respective causes. This approach facilitates and automates the use of expert domain knowledge in the selection of relevant variables to manage the complexity of increasingly data-rich production environments. It limits, however, the applicability of the approach in exploratory analyses, which are complementary to the developed approach.

Future Work. *Scalability.* To evaluate the scalability of the system, we plan to introduce and test the DS-PQA approach for a wider range of joining work cells of different sizes.

Reuse of digital shadow models. We plan to investigate the reuse of digital shadow models for similar but different machines, processes, or products by generating a basic digital shadow model from a historic FMEA+PPR model as a foundation for contextualization.

Acknowledgment

The financial support by the Christian Doppler Research Association, the Austrian Federal Ministry for Digital and Economic Affairs and the National Foundation for Research, Technology and Development is gratefully acknowledged. This work has been supported and funded by the Austrian Research Promotion Agency (FFG) via the Austrian Competence Center for Digital Production (CDP), contract number 881843. This work has received funding from the Teaming.AI project in the European Union's Horizon 2020 research and innovation program under grant agreement No 95740.

[9]OPC UA Groups: www.vdma.org/viewer/-/v2article/render/1248676

References

[1] F. Arévalo, C. Tito, M. R. Diprasetya, and A. Schwung, "Fault detection assessment using an extended fmea and a rule-based expert system," in *Int, Conf. on Ind. Inf. (INDIN)*, vol. 1, 2019, pp. 740–745.

[2] K. D. Sharma and S. Srivastava, "Failure mode and effect analysis (fmea) implementation: a literature review," *Journal of Advance Research in Aeronautics and Space Science*, vol. 5, pp. 1–17, 2018.

[3] M. Colledani, T. Tolio, and A. Yemane, "Production quality improvement during manufacturing systems ramp-up," *CIRP Journal of Manufacturing Science and Technology*, vol. 23, pp. 197–206, 2018.

[4] L. Surbier, G. Alpan, and E. Blanco, "A comparative study on production ramp-up: state-of-the-art and new challenges," *Production Planning & Control*, vol. 25, no. 15, pp. 1264–1286, 2014.

[5] R. Schmitt, I. Heine, R. Jiang, F. Giedziella, F. Basse, H. Voet, and S. Lu, "On the future of ramp-up management," *CIRP Journal of Manufacturing Science and Technology*, vol. 23, pp. 217–225, 2018.

[6] *DIN EN 60812:2015-08 - Fehlzustandsart- und -auswirkungsanalyse (FMEA) (IEC 56/1579/CD:2014)* , Beuth Verlag Std., 2015.

[7] VDIVDE, "VDIVDE 3682 Formalised Process Descriptions." Beuth Verlag, VDIVDE, 2005.

[8] *IEC TR 62541-1:2020, OPC Unified Architecture - Part 1: Overview and concepts*, Int. Electrotechnical Commission (IEC) Std., Nov. 2020.

[9] Z. Huang, S. Swalgen, H. Davidz, and J. Murray, "Mbse-assisted fmea approach — challenges and opportunities," in *2017 Annual Reliability and Maintainability Symposium (RAMS)*. IEEE, 2017, pp. 1–8.

[10] S. Biffl, J. Musil, A. Musil, K. Meixner, A. Lüder, F. Rinker, D. Weyns, and D. Winkler, "An Industry 4.0 Asset-Based Coordination Artifact for Production Systems Engineering," in *Int. Conf. Busi. Inf.* IEEE, 2021.

[11] Z. Wu, W. Liu, and W. Nie, "Literature review and prospect of the development and application of fmea in manufacturing industry," *Int. Jour. of Adv. Manuf. Tech.*, vol. 112, no. 5, pp. 1409–1436, 2021.

[12] M.-A. Filz, J. E. B. Langner, C. Herrmann, and S. Thiede, "Data-driven failure mode and effect analysis (fmea) to enhance maintenance planning," *Computers in Industry*, vol. 129, p. 103451, 2021.

[13] J. Ramezani and J. Jassbi, "Quality 4.0 in action: Smart hybrid fault diagnosis system in plaster production," *Processes*, vol. 8, no. 6, 2020.

[14] S. Biffl, A. Lüder, and D. Gerhard, Eds., *Multi-Disciplinary Engineering for Cyber-Physical Production Systems, Data Models and Software Solutions for Handling Complex Engineering Projects*. Springer, 2017.

[15] U. Dombrowski, J. Wullbrandt, and P. Krenkel, "Industrie 4.0 in production ramp-up mgmt." *Proc. Manuf.*, vol. 17, pp. 1015–1022, 2018.

[16] M. Schleipen and R. Drath, "Three-view-concept for modeling process or manuf. plants with AutomationML," in *ETFA*. IEEE, 2009, pp. 1–4.

[17] S. Kropatschek, T. Steuer, E. Kiesling, K. Meixner, I. Ayatollahi, P. Sommer, and S. Biffl, "Analysis of Quality Issues in Production With Multi-view Coordination Assets," in *2022 IFAC MIM (in press)*, 2022.

[18] S. Kropatschek, T. Steuer, E. Kiesling, K. Meixner, T. Frühwirth, P. Sommer, D. Schachinger, and S. Biffl, "Towards the representation of cross-domain quality knowledge for efficient data analytics," in *ETFA*. IEEE, 2021, pp. 01–04.

[19] W. Kritzinger, M. Karner, G. Traar, J. Henjes, and W. Sihn, "Digital twin in manufacturing: A categorical literature review and classification," *IFAC-PapersOnLine*, vol. 51, no. 11, pp. 1016–1022, 2018, iFAC Symp. on Information Control Problems in Manuf. INCOM 2018.

[20] *OPC UA for MachineTools*, OPC Foundation Std., Sep. 2020.

[21] R. J. Wieringa, *Design science methodology for information systems and software engineering*. Springer, 2014.

[22] J. Herzog, H. Röpke, and A. Lüder, "Allocation of PPRS for the plant planning in automotive assembly," in *ETFA*. IEEE, 2020, pp. 813–820.

[23] A. Presley and D. H. Liles, "The use of IDEF0 for the design and specification of methodologies," in *Proc. 4th Ind. Eng. Res. Conf.*, 1995.