Smart Resilience Services for Industrial Production

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Kurzfassung

Im Projekt SPAICER sind wir davon überzeugt, dass nur resiliente Unternehmen zukunftsfähig sein können. Ziel des Projekts ist daher die Entwicklung eines datengetriebenen Ökosystems auf Basis lebenslanger und kollaborativer Smart Resilienz-Services (SRS) unter Verwendung führender KI-Technologien und Industrie 4.0-Standards. In diesem Beitrag stellen wir ein Vorgehensmodell zur Spezifikation von SRS vor, die für die industrielle Produktion relevant sind, um ein kontinuierliches Resilienz-Management im Unternehmen zu etablieren. Hierzu kombinieren wir Ansätze aus der Design Science Forschung, dem Requirements Engineering und dem Service Engineering.

Abstract (optional)

In the SPAICER project, we are convinced that only resilient companies can be fit for the future. Thus, the objective of the SPAICER project is the development of a data-driven ecosystem based on lifelong, collaborative and low-threshold Smart Resilience Services (SRS) using leading AI technologies and Industry 4.0 standards. In this paper, we present a method for specifying SRS relevant for industrial production for establishing a resilience business continuity. Therefore, we combine approaches from Design Science, Requirements Engineering and Service Engineering.

1. Motivation

Nowadays in our global and interconnected economy, disruptions in industrial production systems are one of the leading business risks. In general, disruptions and their implications on a production system can be manifold: damaged production facilities resulting from natural catastrophes such as hurricane Katrina, lockdown of economies during the COVID-19 pandemic, trade restrictions due to political conflicts such as the US-China conflict or supply shortages such as those resulting from the Ever-Given container vessel being stuck in the Suez Canal. Hence, managing production systems need to become more and more centered around questions of resilience to withstand the effects of such disruptions. In general, companies are characterized as “resilient” when they are capable of permanently adapting to internal and external changes and disruptions [1].

Tracking the overall performance of the production system, anticipating potential disruptive events and deploying effective measures in advance are among the most crucial capabilities in resilience management of global production systems. However, in a survey carried out by the Deutsches Forschungszentrum für Künstliche Intelligenz GmbH (DFKI), only 35% of the 60 surveyed company representatives stated that they have a systematic resilience management in their company, whereas the majority of 60% saw an urgent need for action under the circumstances that disruptions can occur at least occasionally.

The SPAICER project directly addresses the companies’ urgent need for action with regard to resilience management: SPAICER aims for the development of Smart Resilience Services (SRS). By leveraging leading artificial technologies (AI) and Industrie 4.0 standards, we are confident that SRS can enable companies to anticipate disruptions earlier in time and can help them adapt their production planning accordingly at any time. For instance, in terms of resilience management, the great potential of AI has been investigated in both academia and practice [2,3,4,5].

Yet, despite the general promise of SRS, there is – to the best of our knowledge – currently no standardized approach describing how to develop an SRS. Therefore, SPAICER defined a new design method for the development of an SRS that can immediately be adopted by researchers and practitioners alike. Based on this blueprint we hope to further accelerate the proliferation of SRS in real-world applications.

In this paper, we discuss our 6-step design method for specifying SRS combining proven concepts from Design Science (e.g., Design Thinking), Requirements Engineering (e.g., Service Use Cases) and Service Engineering (e.g., Situation-Service-Fit). As we already applied the 6-step design method, we also reflect on our experience with our use cases and share a first technical proof of concept for an SRS.

2. Smart Resilience Services

Let us think of a supplier in the automotive industry who develops precision products for car and truck engines. As the supplier relies on just-in-time delivery of parts with low inventory levels on-side of its production facilities, the supplier might be particularly vulnerable to disruptions in the supply chain, such as supply shortages of raw materials due to trade barriers emerging from political conflicts or delayed deliveries resulting from an ill-suited transport system [6] - a rather simplified, but realistic scenario to illustrate the underlying concept of SRS. In this scenario, the urgent need for an AI-based SRS becomes clear. SRS are smart services that represent individually conFig.d packages of products and services that improve resilience. In a nutshell, we refer to SRS as an adaptive IT application for a more proactive, data-driven approach to resilience management. To allow for more-informed decisions, SRS leverage large data sets from various sources - sources can be internal or external to a company – and perform “intelligent” analyses, such as identification of disruptions in advance. Introduced as a concept for processing data and providing services to various stakeholders, special emphasis is given to AI-based data analytics components and real-time decision-making by smart services [7,8,9]: For example, generic and specific AI modules that can be applied to data streams according to needs and be aggregated into SRS are required. Generic AI modules provide basic functionalities for SRS such as connecting internal or external data sources, pre-processing sensor data, computing similarity measures, encrypting data (e.g., homomorphic encryption), securing data exchange by means of eContracts etc. Specific AI modules meet domain-driven requirements and satisfy specific needs of SRS characteristics for certain production industries; e.g. (fault) pattern recognition, planning of optimized action sequences, (semantic) representation of data, assets, services, knowledge, etc.

For our above-described scenario, a potential SRS could leverage multiple data (e.g., trend analysis for raw material prices, sentiment analysis for political articles) that are relevant to perform impact analyses on, for instance, whether and when supply shortage might occur. Finally, the SRS could provide recommendations for action such as expanding the supplier network, optimizing order volumes, distributing production to more locations, adjusting inventories and revising engine components (across models). Thus, the SRS helps the supplier to strengthen its resilience significantly.

3. Design Method for SRS Specification

"How should an SRS ‘look like’? What functional space should be encompassed? What relevant problem in industrial production should be solved by the SRS?" When discussing these questions with the interdisciplinary team in SPAICER, different answers were given from experts of process and metalworking industry, platform providers, computer scientists, business people, users and data scientists [10,11]. This ambiguity is due to differences in how experts communicate and understand the same problem. One Challenge was to translate the implicit understanding of all project members and stakeholders regarding the intended system of SRS into explicit requirements understandable to the entire team. Design methods help in coping with this challenge by modeling SRS systems so that they can be analyzed from different perspectives as well as for different purposes [11]. As deficiencies in the analysis and requirements specification phase represent the main reason for failure in IT-related projects (cf. Glass' law, Boehm's first law), we searched for a method for bringing experts and various stakeholders "around the table" to develop a common understanding of what problem should be solved by SRS.

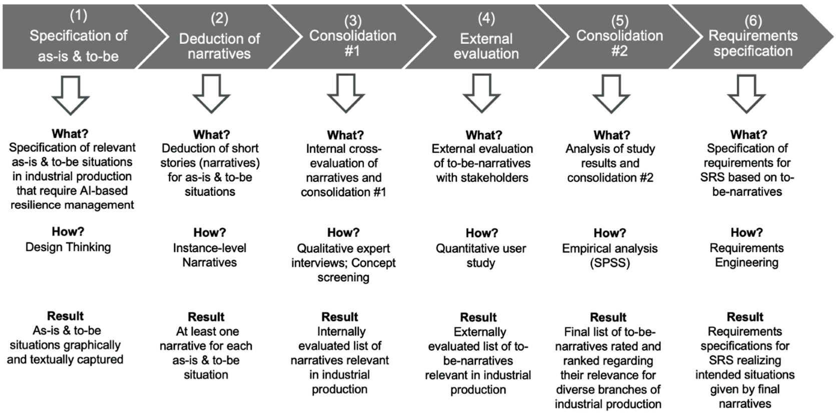

Fig. 1: Design method for specifying smart resilience services

Existing engineering methods from Design Science (e.g., User-Centered Design (UCD), Participatory Design, Design Thinking), Artificial Intelligence [12], Requirements Engineering (e.g., KAOS, i* model, scenarios) [13,14,15,16] and Software Engineering (e.g., Rational Unified Process, Prototyping, SCRUM) lacked an explicit analysis phase with structured procedure for step-by-step development of the desired functional space in the team and/or were not responsive to the central role of data and AI components within SRS. Therefore, we introduced a design method for specification of AI-based SRS according to the needs of the interdisciplinary project team (cf. Fig. 1). Within the method we combine approaches from design science (Design Thinking, narrative thinking), information systems (qualitative / quantitative studies and focus groups), product development (concept screening) as well as from requirements engineering. Consisting of six phases, we started phase 1 with the specification of relevant as-is and to-be situations in industrial production that require future AI-based resilience management.

In our specific case, we started with three broad use cases for which SRS are to be developed that span across various parts of an organization from a micro to macro level. At micro level, planning horizons are local (e.g., on the machine), at meso level they are company-wide. Last, at macro level the whole value chain of the company is considered from a network-oriented perspective. In phase #1, we conducted a Design Thinking workshop working in four groups focusing on industrial resilience issues. Each group was characterized by a mix of experts of process or metalworking industry, platform providers, computer scientists, business people, users and data scientists. As a result, the team specified four as-is-situations representing the status quo and the issue to be solved as well as four to-be situations answering the question “If AI-based resilience management already existed, how would it be used?”. All situations were captured graphically and textually. Within the next sections, the phases #2-#6 as well as outcomes will be elaborated.

4. Deduction of Narratives

Next, within each use case, as-is and to-be situations (phase #1) are defined and of short stories (narratives) described as part of a conceptual modelling method. Conceptual models are means by which a designer expresses his or her understanding of an envisioned information system such as our SRS. In our case, the goal of especially the to-be narratives is to answer the question “If the SPAICER platform already existed, how would it be used?”. In the context of information systems design, narratives are a natural form for describing situations of intended information systems using textual descriptions [17]. They are short stories that describe which actors interact with the service or one another. Studies have shown that the more structured a conceptual language, the better the mental representations and, consequently, the learning and recall results [18]. They are significantly more effective than general-purpose conceptual modeling languages with respect to comprehent and recall of concepts and relationships [18]. Additionally, they are suitable for the external evaluation by experts from various sectors of the manufacturing industry in phase #4 due to their advantages specified above. Therefore, we used the concept of narratives for both, the as-is and to-be situations. For the deduction of narratives, we defined five criteria:

(1) Focus on situation entities (roles, information, environment) and their interactions

(2) Description on instance-level, not type-level
(3) No technical or implementation-related aspects
(4) Understandable for everyone
(5) Short and sweet

Based on the four as-is and four to-be situations, each group that were formed during the design thinking workshop worked on the derivation of the narratives. First, the groups used brainstorming sessions to break the as-is and related to-be situations down into relevant situations focusing on very specific and single industrial processes. Then, each group generated instance-level narratives for each specified industrial process by following the criteria mentioned above. As a result of phase # 2, a list of narratives for each as-is & to-be situation has been derived (in total = 14 as-is and 14 to-be narratives).

Within the subsequent consolidation (phase #3), an internal cross-evaluation of narratives was conducted (cf. Fig. 1). Therefore, narratives for as-is and to-be situations of AI-based SRS were discussed with business partners and experts from process and metalworking industry. Objective of these qualitative interviews was to capture the relevance of SRS described in narratives with respect to the daily business of experts. Results of interviews showed application opportunities of SRS in further industrial domains as well as potential for ideation, e.g., forming hybrids of two narratives. For combining qualitative interviews with a quantitative approach for consolidation, we applied concept screening methods from product development for addressing multi-criteria decision problems, e.g., Pugh Controlled Convergence Method [19,20]. Therefore, a screening matrix “narratives of to-be situations vs. criteria” was set up. Criteria are independent in concept screening and represent a kind of target specification. In our case, we defined five criteria:

(1) Compliance with SPAICER; i.e., narrative describes a to-be situation of AI-based resilience management
(2) Relevance; i.e., narrative describes an issue whose solution is relevant and challenging in industrial production
(3) Research gap; i.e., narrative describes a scientifically demanding topic whose solution goes beyond existing state of the art
(4) Feasibility; i.e., narrative describes a usage situation of a service that can be prototypically implemented within the next year
(5) Innovation; i.e., narrative indicates a technical solution of AI-based resilience management in industrial production going beyond and being not comparable with any existing system or out-of-the-box solution at market

In absence of a unique reference concept, evaluation of narratives was conducted by rating them with “+”, “-“ and “o” with respect to the whole set of narratives as well as given criteria. In case of “o” either the narrative’s value was quite similar to other narratives or the difference towards other narratives was controversial. Because additional information was required, the narratives were rated in a workshop with all stakeholders, i.e. the mix of experts of industrial production, platform providers, computer scientists, business people, users and data scientists. Special emphasis was given on ratings by business people and experts of industrial production in case of criteria (2), on ratings by R&D people for criteria (3), as well as on ratings by platform providers for criteria (4). The purpose of counting the points was not to identify a single winning narrative, but to reduce the number of narratives, i.e. eliminate weak concepts, form hybrids or gain a better understanding of SRS design issues. As a result, a consolidated and internally evaluated list of six final narratives was specified (cf. Table 1):

Table 1: Consolidated and internally evaluated list of six final narratives relevant in industrial production

Narrative 1: Machine parameter optimization to avoid defective prefabricated components A plant operator supervises the manufacturing process of prefabriced components on a plant. At the beginning of order processing, the plant reports and visualises recommendations for parameter optimization to the plant operator, such as optimal infeed and outfeed settings. The recommendations are based on analyses of the manufacturing parameters as well as sensor-based measurements on the raw material. The line operator releases the parameters for the line. After testing the first finished parts, which are completely in order, series operation can be started directly.
Narrative 2: Wear prediction for cost-effective tool maintenance and avoidance of downtimes A manufacturing process on a plant takes place continuously without disturbances. Relevant signal parameters of the plant are recorded in the background. The system reports and visualises: "Deviation 20% from normal system status, frequency range atypical! Repair of tool XYZ recommended!" The tool is removed, brought to an optimal condition and reinstalled. In the newly started series process, the proactive maintenance of the tool means that there are no out-of-order parts, the active elements of the tool can be reused many times through timely reworking and downtimes due to tool maintenance have been reduced.
Narrative 3: Knowledge transfer to avoid wrong decisions and additional costs An experienced employee supervises a manufacturing process at a plant. Accompanying the manufacturing process, the employee's expert knowledge is continuously recorded. The machine asks for feedback in the form of problem-solving patterns and process step evaluations and checks the plausibility of this information. When the experienced employee is absent and has to be replaced by an inexperienced colleague, a problem occurs on the line. The machine recommends a course of action: "Jammed part in the tool. Problem has already occurred frequently. Cleaning and additional use of non-oil fluid HLW3000 solved the problem on 13 June.2020." Through the transfer of knowledge, the problem can be solved quickly and optimally despite the lack of experience of the representative.
Narrative 4: Analysis of the consumer market to proactively adjust production planning. A company relies on analyses of the relevant consumer market in its strategic planning. A system

proactively provides regular detailed forecasts on the development of the consumer market (e.g. for the mobile phone and camera sectors). The forecasts are based on the evaluation of various data sources (e.g. export data, interviews, quarterly reports, blogs, etc.). This enables the company to make necessary internal changes and conversions/upgrades in production planning in good time (e.g. arrange for the purchase of additional machines at an early stage).
Narrative 5: Scenario simulation to prepare for external disruptive factors A company is considering relocating one of its production sites. In addition to immediate investment costs, the aspect of "resilience" in particular is to be taken into account when deciding on a relocation. Therefore, the company analyses whether a relocation can contribute to an improvement or deterioration of the company's resilience. For this purpose, the risk management system simulates economic risks (e.g. financial crises), environmental and natural risks (e.g. earthquakes) as well as geopolitical risks (e.g. trade strike), social risks (e.g. poaching of skilled personnel), health risks (e.g. pandemics) and technological risks (e.g. cyber attacks). Based on the simulation, the company receives recommendations for action for setting up a new location.
Narrative 6: Signal analysis to secure and optimize supply of raw materials For the production of a prefabricated components, the security of supply with raw materials plays a decisive role, as the machines cannot be temporarily switched off or changed over to another finished part. In order to be able to recognize potential risks such as delivery failures at an early stage, the buyers use a system that filters relevant sources of information regarding raw materials, suppliers, countries, etc. based on preferences, bundles messages and examines them for signals that could have an influence on the company's raw material supply. At the same time, the purchasing department can evaluate the relevance of displayed messages, so that the system is constantly improving. This saves time, as purchasing can quickly check and evaluate notifications from the system to secure the supply of raw materials.

5. External Evaluation

To conduct an external evaluation of the internally consolidated narratives by experts from various sectors of the manufacturing industry as the stakeholders of our planned SRS, we designed a quantitative study. The study was conducted in form of an online study. The participants had to read the six narratives describing AI-based resilience management and rate each narrative according to how well it would fit into the participant's everyday work routine. For the rating scale, an unforced bipolar seven-point Likert scale ranging from "1 = I completely disagree with the statement" to "7 = I completely agree with the statement" has been used. To get a first idea of the trend, we aimed to reach n > 30 [21]. In total, 33 subjects participated in the online study. The respondents came from wide range of industries with, with the top 3 industries being the manufacture of motor vehicles and parts (21%), mechanical engineering (18%) and leather manufacturing and production (12%). 65 % of the participants are working in enterprises located in Germany, whereas 13% are located in Europe and 22% worldwide. For this effort, we involved participants with deep knowledge of their respective industries to quickly get a good overview. This being said, the majority of the participants have more than 8 years of working experience (74%), are over 45 years of age (54%) and work in big enterprises with ≥ 250 employees (58%). The results show that all six narratives seem to be relevant for the manufacturing industry (mean of every narrative >4.00). Moreover, narrative 2 has the highest relevance amongst the presented narratives (mean = 6.06, SD = 1.06) followed by narrative 1 (mean = 5.88, SD = 1.24). Therefore, it can be concluded that narrative 2 is perceived being the most relevant for the participants' everyday working routine. Narrative 4 "Analysis of the consumer market to proactively adjust production planning" has been rated as the least relevant narrative (mean = 4.85, SD = 1.56).

Table 2: Relevance Assessment of Narratives

	Narrative 1	Narrative 2	Narrative 3	Narrative 4	Narrative 5	Narrative 6
Mean	5.88	6.06	5.82	4.85	5.12	5.13
SD	1.24	1.06	1.07	1.56	1.24	1.50
Variance	1.55	1.12	1.15	2.44	1.55	2.27
Minimum	2	2	3	1	2	1
Maximum	7	7	7	7	7	7
p50	6,00	6,00	6,00	5,00	5,00	5,00

As a result of phase #4 (quantitative user study), we received an externally evaluated list of to-be-narratives relevant in the industrial production. After phase #5 (consolidation #2), we received a final list of to-be narratives rated and ranked regarding their relevance for diverse branches of industrial production. Thus, in the following section, we present the requirements specification for to-be narratives exemplarily for narrative 2 as being evaluated as the most relevant narrative amongst all presented narratives.

6. Requirements Specification

Based on first trend results of phase #5, we started the requirements specification based on the list of to-be-narratives in phase #6 (cf. Fig. 1). For realizing application scenarios of AI-based resilience management as described by the narratives, underlying information systems are required. Information systems are compounds of social systems, information spheres, and service systems that use information technology infrastructures for the realization of desired situations, as given by narratives [22,23]. In extension to information systems that exclusively process information objects, design models for information systems embedded in physical environments also require means for representing physical entities (e.g., IoT infrastructures, sensors). Adopting the Abstract Information System Model (AISM) representing a conceptual, i.e., logical description of information systems, we focused on four layers during requirements specification: information sphere, social system, service system and physical object system [24] Information sphere covers a set of information objects used within the realm of the IS, e.g., raw data streams and aggregated data products (cf. GAIA-X data assets). The social system represents a set of roles available with rights, obligations, and prohibitions. In context of SPAICER, users of SRS can take multiple roles, e.g., data owner, provider or consumer of SRS etc. (cf. GAIA-X roles of participants [25]). Third component - the service system - covers the set of services available within situations in which the information system can be used, i.e., SRS that enables wear forecasting but also service modules realizing helper functions (cf. GAIA-X services and service instances). Last, the physical object system defines the set of physical entities available within situations in which the information system can be used. In SPAICER, this applies to IoT devices and sensors across production lines that produce raw data streams as well as entities offering interfaces to SRS (cf. GAIA-X nodes). Based on this four-piece pattern, narratives were analyzed regarding information objects, actors and roles, services and physical objects during requirements specification. Table 3 shows exemplarily the specification of requirements for narrative 2 based on the aforementioned pattern.

Table 3: Requirements specification of narrative 2 with respect to information objects, actors and roles, services and physical objects (cf. [24])

<table>
<tr><td rowspan="2">Information objects</td><td>(Which (raw) data / data streams are required / already available?)
• Sensory data in form of time series (temperature, sound etc.) of production run
• Machine type (machine ID)
• Specification of used raw material
• Characteristics of materials (quality control etc.)
• Machine parameters</td></tr>
<tr><td>(Which aggregated data products are required / already available?)
• Aggregation of time series data (variance, mean values etc.)
• Used tools (age in form of cycles, cycles since last maintenance, number of maintenances, etc.)
• Interruptions (duration, reasons)</td></tr>
<tr><td>Roles</td><td><table>
<tr><td>x</td><td>Data provider (Manufacturer of raw material, producer)</td><td>x</td><td>Data owner (Manufacturer of raw material, producer)</td></tr>
<tr><td>x</td><td>Service consumer (machine/systems operators, quality assurance manager, production manager)</td><td></td><td>Service provider</td></tr>
<tr><td></td><td>Service instance provider</td><td>x</td><td>Node provider (Manufacturer of raw material, producer)</td></tr>
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Interface services	*(Which interface services with direct user interaction are required?, e.g., SRS)* • Wear forecasting with information about propagation of the fault into subsequent processes • Action Recommender (generation of recommended actions (with probability of success), e.g., based on error messages, problem reports in repair diary) • Feedback Integrator (recording and integration of user feedback (e.g., in case of detected anomalies)) • Visualizer (generation of graphical representations based on generated results, e.g., diagrams, traffic light representations, etc.) • Communicator (generation of textual or dialog-based representations of results or request options with regard to SRS offer)
Internal services	*(Which internal services without direct user interaction are required?, e.g., internal service modules)* • Data Preparation (collection, aggregation, and preparation of sensor data/raw data for use in SRS) • Annotator (semi-automatic description / annotation of data as well as roles and services where applicable) • Local and global anomaly detection • Explanation Generator (present explanations for recommendations for action, forecasts, etc. (Explainable AI)) • Performance Indicator (illustration of success rate of SRS: predicted results vs. reality) • Data Observer (monitoring availability of data streams / sensors and dealing with missing data (while checking remaining forecast quality))
Physical objects	*(Which IoT devices / sensors are required to produce data streams and/or realizing SRS interface?)* • Sensors for measuring machine parameters (temperature etc.) • Acoustic emission box (sound emission data) • IoT devices for realizing SRS interface (e.g., tablet, display on the machine)
Objective	*(How does the SRS contribute to resilience optimization?)* • Predicting production line malfunctions/maintenance requirements for cost-effective maintenance and avoidance of downtimes

As a result of phase #6, we received requirements specifications for SRS realizing intended situations given by the final narratives. Serving as starting point for detailed technical specifications, based on determined information objects data-oriented requirements can be derived. Identified actors and roles can be applied for specifying non-functional requirements whereas interface and internal services represent the starting point for determining functional requirements.

7. Future Work

Application and results of our 6-step method showed that the approach can significantly help in developing innovative SRS relevant in various industries. For validating results of the trend analysis and for capturing critical technical risks identified at service level at an early stage, a first technical proof of concept for resilience optimization of production machines through AI-based wear prediction (cf. narrative 2) was implemented (see Fig. 2). For process industry a SRS was prototypically implemented that enables reduction of production failures and costs by avoiding wear and production downtime. The SRS helps (1) in monitoring wear of components, (2) to detect drifting of process states from "normal state" at an early stage, and (3) to be able to intervene. Various sensors are installed in the production system that continuously transmit data. The service analyzes these data streams in real time locally for individual process sections using AI-based anomaly detection, provides anomaly metrics and aggregates them into a global view of the production line respectively the current production run. The SRS reports an anomaly in this section, indicates that no action is required, and asks for feedback from the operator (reinforcement learning). Thereby, the SRS thus enables a production run to be stopped in time before product quality deteriorates as well as targeted and local repairs or changes of components by detecting local anomalies in specific process sections.

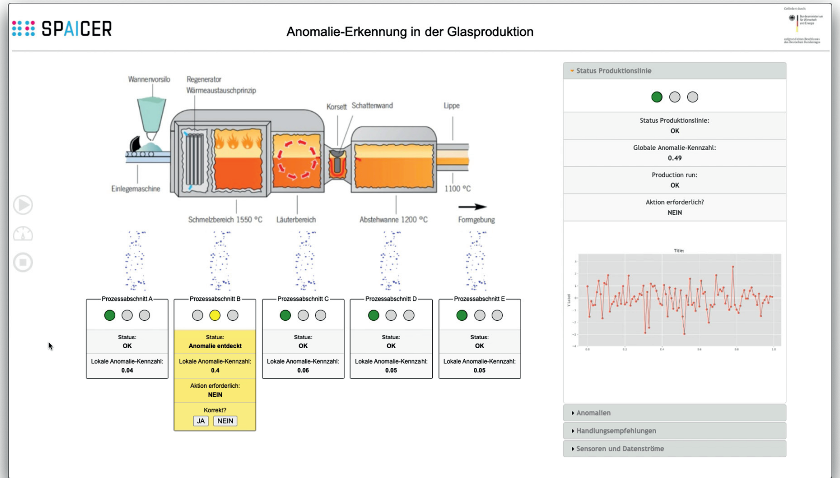

Fig. 2. Proof of concept of smart resilience service on wear protection described by narrative 2

Based on our first trend analysis, additionally planned workshops for further evaluation of our narratives as well as requirements specifications, we will: (a) develop PoCs for challenging technical issues generated from narratives identified as being the most relevant for production industry, and (b) implement SRS according to results of PoC developments. For implementing SRS on a SPAICER platform compliant with GAIA-X, reference implementations of AI core modules are planned where necessary modules will be incrementally integrated in SRS, tested, and optimized. Thereby, a successful deployment of relevant SRS for production industry on the envisioned SPAICER platform will be realized.

8. Literature

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