Human-in-the-Loop Control Processes in Gas Turbine Maintenance

Michael Barz[1], Peter Poller[1], Martin Schneider[2], Sonja Zillner[2], and Daniel Sonntag[1]

[1] German Research Center for Artificial Intelligence (DFKI), Campus D3.2, D-66123 Saarbrücken, Germany
`{firstname.lastname}@dfki.de`

[2] Corporate Technology Siemens AG, Otto-Hahn-Ring 6, D-81739 München, Germany
`{firstname.lastname}@siemens.com`

Abstract. In this applied research paper, we describe an architecture for seamlessly integrating factory workers in industrial cyber-physical production environments. Our human-in-the-loop control process uses novel input techniques and relies on state-of-the-art industry standards. Our architecture allows for real-time processing of semantically annotated data from multiple sources (e.g., machine sensors, user input devices) and real-time analysis of data for anomaly detection and recovery. We use a semantic knowledge base for storing and querying data (http://www.metaphacts.com) and the Business Process Model and Notation (BPMN) for modelling and controlling the process. We exemplify our industrial solution in the use case of the maintenance of a Siemens gas turbine. We report on this case study and show the advantages of our approach for smart factories. An informal evaluation in the gas turbine maintenance use case shows the utility of automated anomaly detection and handling: workers can fill in paper-based incident reports by using a digital pen; the digitised version is stored in metaphacts and linked to semantic knowledge sources such as process models, structure models, business process models, and user models. Subsequently, automatic maintenance and recovery processes that involve human experts are triggered.

Keywords: Cyber Physical System (CPS), Human-in-the-loop, Industry 4.0, Smart Factory, Case Study, Handwriting Recognition, Gesture Recognition, Anomaly Handling, Business Process Model and Notation (BPMN), Anomaly Detection, Semantic Knowledge Base

1 Introduction

Human-computer interaction for control processes is one of the key development issues in cyber-physical systems (CPS) [6]. Especially in industrial settings, incorporating workers in the manufacturing process as *humans-in-the-loop* is promising for decision-making [5,27]. Further, efficient and secure manufacturing requires the standardisation of business processes [13].

In this paper, we propose a cyber-physical system (CPS) architecture for smart factories enabling a real-time semantic data analysis from multiple sources, which is controlled by a standardised BPMN model (see also [16]). We evaluate our method in the use case of gas turbine maintenance. Maintaining industrial facilities is of high relevance—it helps to significantly reduce operating costs and to improve productivity of the plant operations and the quality of the product [1]. However, as of today, the integration of production and maintenance processes is only realised and implemented in a very limited way. With the increase in automation, electrification, and digitalisation of plants, more and more monitoring and maintenance devices and applications in cyber-physical environments are emerging. In this way, single parts or components of plants are serviced by dedicated predictive maintenance applications. In general, those techniques should complement preventive maintenance strategies (i.e., strategies including predetermined periodic basis components of the plant that are taken off-line for inspection.) In addition, due to the complexity of the underlying processes and operations, employees that are most experienced with handling the machines and plant components are no longer actively involved in the maintenance process. In summary, the following shortcomings in maintenance applications on plants at various levels can be observed[3]:

- The **knowledge and expertise of production employees** is no longer integrated in an effective manner in the maintenance process.
- Many separate **monitoring applications** provide important insights about plant components. However, often they do not include a comprehensive view on the plant performance.
- The **semantic knowledge** about the plant structure and its basic principles are not incorporated into the maintenance processes.

With our CPS architecture, we provide an approach to overcome these limitations. It supports a seamless alignment of human-generated expert know-how with machine-generated maintenance know-how in a semantically consistent manner for improving the analytic-based maintenance application. In particular our system enables: (1) a seamless integration and processing of expert knowledge by smart pen technology (directly transferred from [23,21,22]); (2) modelling and executing of workflow knowledge in form of BPMN [15] models; (3) incorporating structural knowledge about the plant and its operations by means of a semantic model (semantic modelling/storage of components, products, and reports in metaphacts); and (4) usage of this integrated data source as input for analytical applications aiming to produce new valuable insights and to trigger automatically recommended actions.

2 Related Work

A general overview for the current status and the latest advancement of CPS in manufacturing is given in Wang et al. [26] and Sonntag et al. [24]. Herman

[3] We extracted these shortcomings from interviews with domain experts.

et al. [7] analysed literature on Industry 4.0 scenarios, which include CPS, and extracted essential design principles for such systems. Our system complies with *Interoperability* by incorporating humans-in-the-loop, *Virtualisation* by modelling processes with BPMN and with *Decentralisation*, *Real-time capabilities*, *Service orientation* and *Modularity* given by our flexible smart factories server infrastructure. Wang et al. [25] introduce an Intelligent Predictive Maintenance (IPdM) system targeting zero-defect manufacturing in smart factories. They include preventive and predictive maintenance approaches [1], but lack from incorporating the workers that can provide valuable inputs. Zamfirescu et al. [27] introduce a reference model for anthropocentric cyber-physical systems (ACPS). They consider the worker as a composite factor of a general hybrid manufacturing system ("human-in-the-loop"). We adhere to the "human-in-the-loop" principle and build the platform for a holistic IPdM system in our maintenance scenario.

Petersen et al. [17] present a semantic model for representing smart factories as ontology instances. However, their system is limited to monitoring applications. In contrast, our system allows us to trigger relevant actions upon monitoring events. Mayer et al. [14] propose the Open Semantic Framework and show its utility for increasing worker safety in industrial settings. Both publications rely on standards concerning the semantic knowledge representation, but lack a standardisation for the business processes in which they are integrated. A very good and comprehensive overview for industrial standards mapped to the ISA95 model[4] is given in Lu et al. [13]. Furthermore, Lee et al. [12] propose a guideline for implementing Industry 4.0-based manufacturing systems similar to the ISA95 model and defined a sequential workflow order of implementation for two major functional components of a CPS. Our case study is an ISA95 model level 3, similar to Panfilenko et al. [16].

3 Technical Architecture

Our goal is to implement a system architecture that allows us to integrate, align, analyse, and manage machine and human generated data to produce faster response times for anomaly recovery. The most important aspect of our architecture is its flexibility with respect to the attached software components and hardware devices facilitating fast adoption to different industrial use cases. We developed a decentralised service-oriented architecture with the *Smart Factories Server* at its core (see figure 1). It serves as request proxy (services can sign up; client requests are processed accordingly) and event broadcasting node (data publisher and subscriber can register). The communication is based on XML-RPC [11]. This approach enables an easy integration of a BPMN engine managing the business processes and a semantic knowledge base providing the necessary concepts of the domain. We use the Camunda[5] BPMN workflow server and the metaphactory platform of metaphacts[6]. Further, it allows for a seamless

[4] www.isa.org

[5] Camunda, `https://camunda.org/`

[6] Metaphacts, `http://www.metaphacts.com`

integration of any user input device and machine sensor streams as data publisher. In particular, we integrated smart pens with networking capabilities and machine sensors. The following section provides further details about a concrete use case implementation.

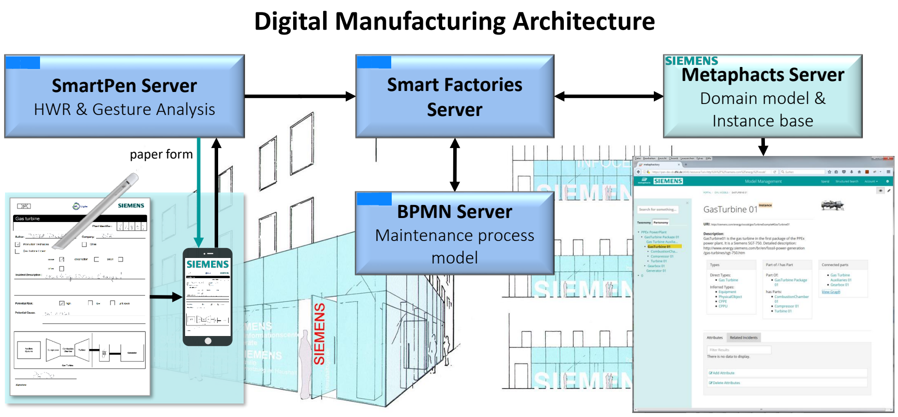

Fig. 1. Smart factories server architecture, see the use case video on the *GALLERY* tab: http://dfki.de/smartfactories

4 Use Case

Anomaly detection and recovery is of high relevance in manufacturing as failures lead to high cost. In industrial environments, anomalies are usually detected by workers or technicians that are familiar with the production facility; this includes visitors from other organisational units with technical knowledge. Another approach is the automated detection of anomalies through automatic analysis of data from sensors monitoring the production processes. However, such systems are often constrained to a single component whereas a failure would propagate to interconnected components, for example in a production line. Due to the high flexibility end extensibility of our CPS architecture, it can be applied for improving these and multiple other scenarios. In this section, we describe the use case of *gas turbine maintenance* and emphasise the potential of our architecture with a focus on human-in-the-loop error recovery.

4.1 Gas Turbine Maintenance

This business scenario focuses on the operation and maintenance of gas turbines, in particular, we considered the Siemens gas turbine (SGT-750) as reference object. We focussed on seamlessly incorporating workers in the maintenance process (human-in-the-loop) without the need for workers to change their daily practice. The maintenance processes, which were elaborated in extensive expert interviews, are modelled with BPMN (see figure 2). This standardisation is central to our approach. To this end, a BPMN engine manages all incidents based on this model as indicated in figure 1. The model further includes the integration of humans into the workflow. The human-in-the-loop functionality allows a worker to fill in paper-based incident reports with a smart pen, or to call a technician in the case of high risk incidents. A detailed description of all components is provided next.

4.2 Implementation

In this section we describe the core aspects, major components and functionalities of our implementations for the gas turbine maintenance use case. These include the standardised BPMN workflow models, the pen-based incident reporting for integrating humans-in-the-loop and the underlying semantic modelling and knowledge representation (see figure 1). The target is to automatically process incident reports and, depending on how critical the case is, to intervene in real-time by alerting experts. The individual software components were designed and implemented in close cooperation with domain experts, especially concerning the BPMN-based workflow and the semantic models. We illustrate one possible implementation of our general CPS architecture.

Gas Turbine Maintenance BPMN 2.0 Model The maintenance processes including the handling of incident reports are realised as BPMN process models, which were elaborated in expert interviews. We use the Camunda BPM server for automatically mapping reported incidents to maintenance steps of the gas turbine in real-time (see figure 2). The process can be explained as follows: first, an incident is observed in a facility, which yields a filled report modelled as a BPMN event. It is evaluated by our classification components, and a report page is inserted into the metaphacts knowledge base. Further, "proceed to further processing" keeps record and passes the incident on to the next decision point. Eventually, "compute risk" calls a risk level assessment (in the current model *high* and *low*). Depending on the risk level, user tasks (human-in-the-loop) and automated activities are initiated. If the risk is low, the Remote Diagnostic Center (RDC) shall be notified via email and the production technician, who can manually adjust the configuration, is informed. In case of a high risk, a service expert is called and the RDC department receives an alert. A use case video helps to understand this process of anomaly detection within a distributed digital manufacturing architecture.[7]

Smart Pen Technology In the industrial context, the interaction with pen and paper forms is well known to the users and fits into established business processes, e.g., documentation, maintenance, repair, or reporting processes. Thus,

[7] Smart Factories, `http://dfki.de/smartfactories/?page_id=82`

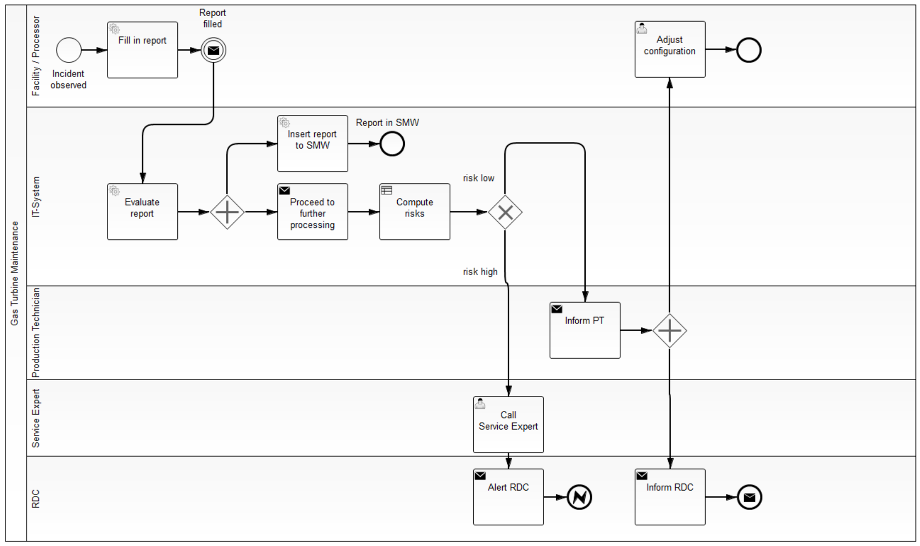

Fig. 2. Gas Turbine Workflow Model in BPMN 2.0

introducing the digital pen technology for these tasks requires only low training effort and cost. The major advantage of smart pens is that the acquired data can be processed and integrated in real-time into corresponding software systems which enables continuous knowledge acquisition with worst-case execution time (WCET) capabilities. We use the highly innovative and networked *Neo Smartpen N2* facilitating digital user interaction on specially prepared papers [20]. These special paper forms contain an almost invisible grid structure for identification of the form and localisation of the pen strokes. A filled paper form is immediately synchronised via Bluetooth or Wifi with the screen of an iPhone or tablet computer (DFKI provides additional streaming technology). On confirmation by the user, the raw data is sent to the *SmartPen Server* which is responsible for detecting the form and for managing the handwriting and stroke gesture analysis. The handwriting recognition and gesture/shape analysis is performed by using a commercial software library integrated into our system architecture (myscript.com).

Preparation of Domain Specific Paper Sheets The individual data fields have been derived by intensive discussion with our technology partner Siemens and can be described as follows: author and company name are important data for further incident tracing and recommendation for task assignments; the identity of the author influences the reliability of provided risk estimates, e.g., technicians know the production line from daily work while service experts possess a much deeper knowledge of the technology; incident type and description provides a simple classification; potential risk gives subjective user risk assessment. The

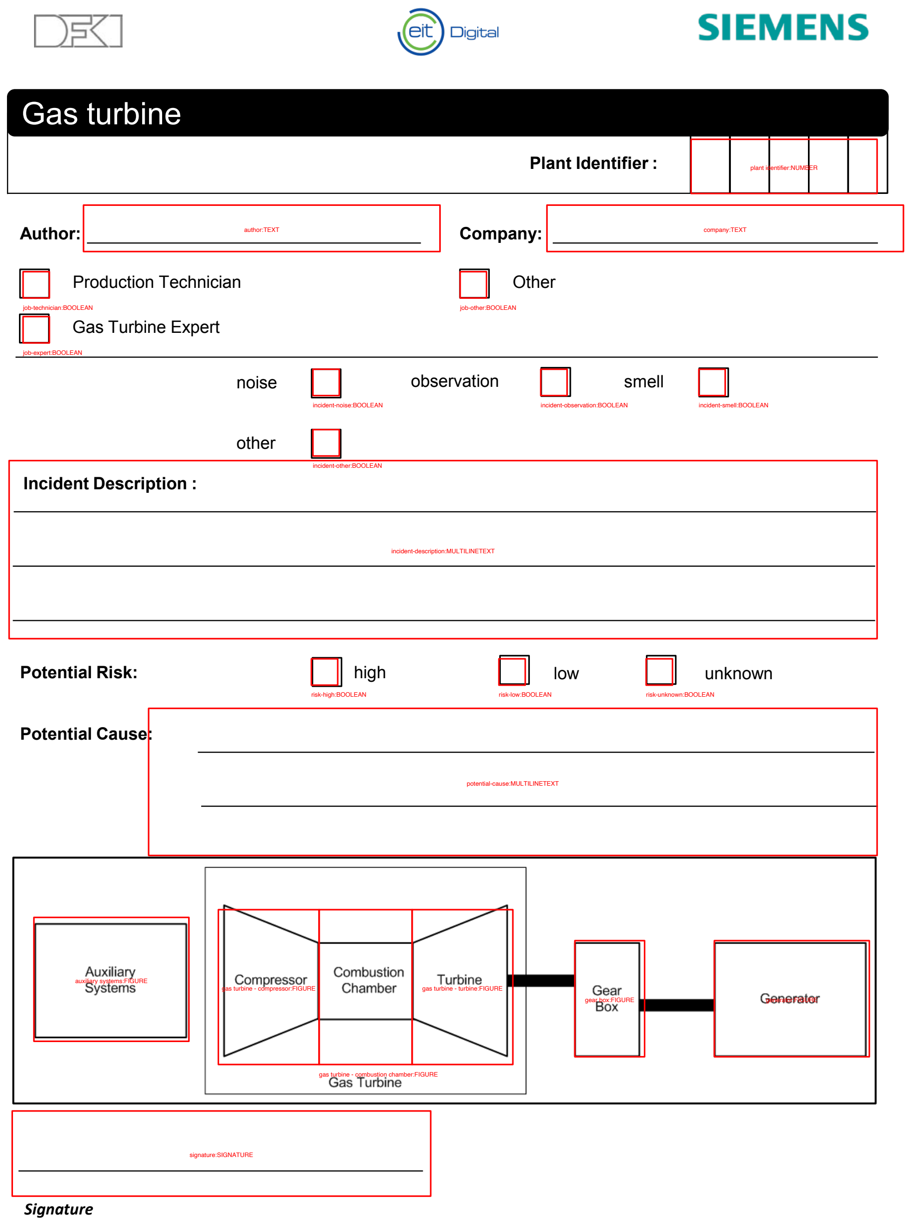

Fig. 3. Specification of the semantics of the gas turbine maintenance report

graphical sketch representation is used to enable the workers to easily locate the incident by marking it on the printed illustration of the machine. The layout of the sheet has been determined in close cooperation with layout designers and experts of the application domain. We identified checkboxes, handwritten text, and encircling or marking components on a symbolic sketch with a pen gesture as efficient input methods. Figure 3 shows the gas turbine maintenance sheet and the individual regions for handwriting input on it. The semantics of the form is defined by the geometric location, the input type and the underlying domain and report model of all fields (highlighted in red). The gas turbine maintenance report includes the following semantic regions:

– TEXT: "plant identifier", "author", "company", "incident-description", "potential-cause", "signature"
– CHECKBOX: "job-technician", "job-expert", "job-other", "incident-noise", "incident-observation", "incident-smell", "incident-other", "risk-high", "risk-low", "risk-unknown",
– GESTURE: "auxiliary systems", "gas turbine - compressor", "gas turbine - combustion chamber", "gas turbine - turbine", "gear box", "generator"

Semantic Knowledge Base—Metaphacts We use metaphacts as underlying semantic knowledge base which is based on the standards OWL for modelling and HTML5 for visualisation. It incorporates a semantic database Blazegraph[8] for storing data in terms of the Resource Description Framework (RDF)[9] triples (triplestore). A wiki that presents data to end users (e.g., incident reports) is connected to the database by the SPARQL Protocol and the RDF Query Language (SPARQL) [19]. A core advantage of metaphacts is this semantic representation of data and the presentation that is based on the underlying concept models. This allows for a more efficient development of semantic applications compared to similar products, e.g., to the Semantic MediaWiki (SMW) [10] that was used by Panfilenko et al. [16]. The SMW extends MediaWiki with simple semantic capabilities, but remains a wiki which focusses on web pages.

We semantically defined our maintenance architecture in metaphacts with a specific procedure model for anomaly detection and incident reporting. It is integrated into all related plant structures and I2MSteel[9] knowledge models. There are generic templates for anomaly instances and incident reports specifying generic concepts without defining the details. The specification of the details (e.g., presentation type, form structure, relevant properties) is done for the concrete subtypes, e.g., a company, a specific plant or production components and machines.

In metaphacts, existing OWL models (created with Protégé for example) can be uploaded to the metaphactory and templates can be developed via a browser interface. For uploading instances to the knowledge base (i.e., the semantic data from a digitised paper report) we use the corresponding RDF SPARQL

[8] Blazegraph, `https://www.blazegraph.com/`
[9] I2MSteel, `https://www.cetic.be/I2MSTEEL`

commands transmitted via metaphacts' REST interface and the standard turtle/TTL syntax (see the example below). The ttl description includes a header defining the namespace prefixes and the semantic data triples that were extracted from the incident report. The corresponding PDF document is uploaded to the knowledge base as reference and integrated into the resulting incident report page (see figure 4). Here's an Turtle/TTL example:

```
@prefix: <http://siemens.com/energy/vocab/gasTurbineExample#>.
@prefix gtd: <http://siemens.com/energy/schemas/gasturbineDomain#>.
@prefix owl: <http://www.w3.org/2002/07/owl#>.
@prefix rdf: <http://www.w3.org/1999/02/22-rdf-syntax-ns#>.
@prefix xml: <http://www.w3.org/XML/1998/namespace#>.
@prefix xsd: <http://www.w3.org/2001/XMLSchema#>.
@prefix ppex: <http://siemens.com/energy/vocab/gasTurbineExample#>.
@prefix rdfs: <http://www.w3.org/2000/01/rdf-schema#>.
@prefix report: <http://siemens.com/reporting/schemas/generic#>.
@base <http://siemens.com/energy/vocab/gasTurbineExample>.
### http://siemens.com/energy/vocab/gasTurbineExample#TestReport_02:TestReport_02
rdf:type report:IncidentReport, owl:NamedIndividual;
rdfs:label "Gas Turbine Report Incident 170314_100508";
report:incidentType "Noise";
report:hasDate "2017-03-14 10:05:08";
report:authorsCompany "Siemens AG";
report:potentialRisk "unknown";
report:authorType "Other";
report:potentialCause "bearings worn out?";
report:author "Schneider";
rdfs:comment "rumbles very much";
report:locatedAtComponent:Generator01;
report:pdflink "/assets/reports/gasturbine/form-44f106ed-f262-4122-941c-b0173160ca8b.pdf".
```

5 Maintenance Case Study

One case study with domain experts is presented to illustrate the usefulness of our service-oriented CPS architecture for industrial applications. In this case study we explore the impact of our approach on the efficiency of maintenance processes in the gas turbine use case. Through interviews and case studies with domain experts, we iteratively designed and realised a seamless integration of workers in the model-driven and standardised workflow using smart pen technology. Incident reports are automatically analysed in real-time based on semantic domain knowledge which initiated proper prevention or recovery activities. We investigate the strengths and limitations of our architecture.

Maintaining industrial facilities is of great importance for reducing cost and for improving product quality. In contrast, state-of-the-art processes in many factories include simple pen and paper forms for incident reporting inducing long processing and thus reaction times. In addition, these reports cannot be used for analysing failures and for extracting their causes. This case study is based on a qualitative assessment of our system extracted from interviews with expert users that tested it in the gas turbine maintenance use case. Key advantages that were reported are:

- Incident reports are immediately digitised, aligned and integrated into the semantic knowledge base (digitalisation) within a few seconds which enables:

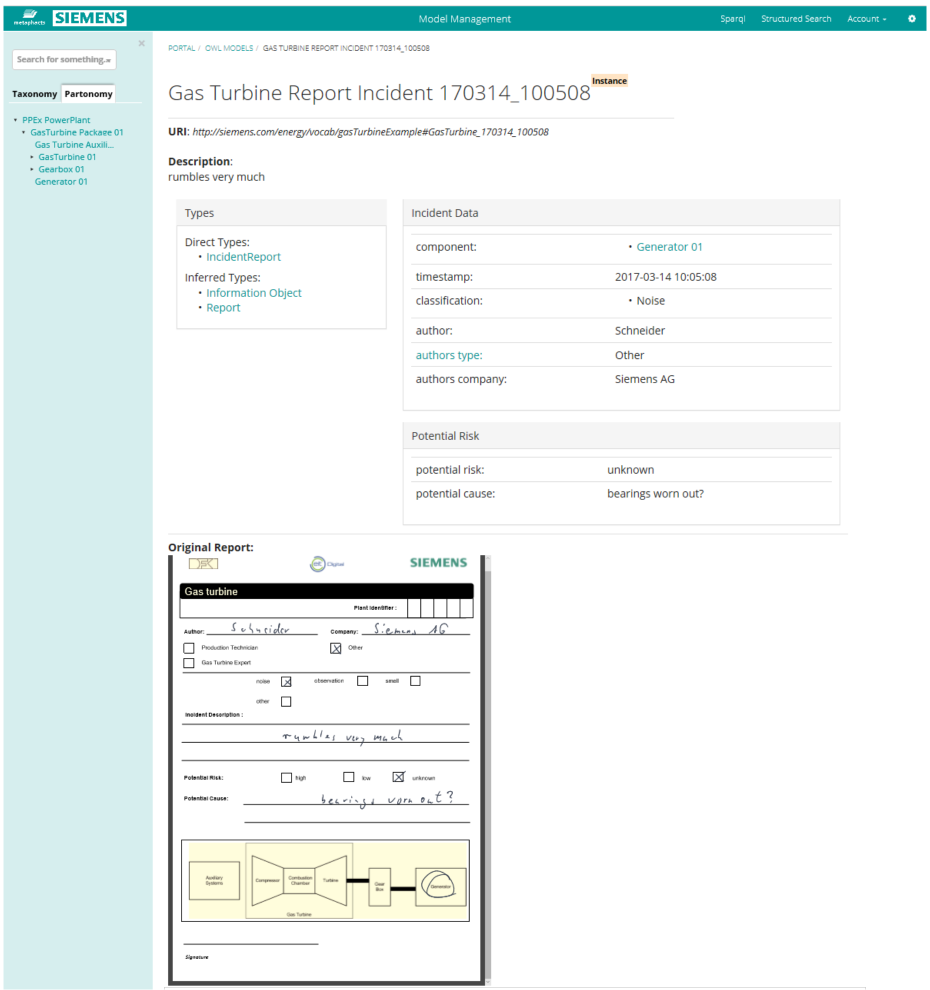

Fig. 4. Incident Report in Metaphacts

  - Immediate data analysis (WCET) and over time, e.g., augmented with sensor data
  - Very fast response times
  - Intuitive and clear visualisation by filtering/searching for incidents with certain criteria (e.g., component, time interval, incident type or keywords within comments)
- Easy alignment to other business processes due to standardisation with BPMN (well established in the industrial domain)
- Low overhead concerning change management as workers are already familiar with pen and paper

Interestingly, in comparison to tablet-based applications, the pen based application was preferred as it was easier to handle and use in the working environment. The experts also mentioned the potential for other industries, such as automotive, that are still relying on analog paper-based reporting. In general, we can state that the future potential of these applications has been recognised by our expert partners in a very positive manner and in nearly all discussions, they mentioned further scenarios and processes that could benefit from this technology.

6 Conclusion and Outlook

We proposed a service-oriented architecture for seamlessly integrating workers in industrial cyber-physical production environments. This enables automatic data processing based on standardised models (BPMN and semantic concepts). A case study with domain experts (maintenance processes for a gas turbine) has shown the usefulness of our approach. It also demonstrated the flexibility of our architecture and thus its potential for improving efficiency in many other Industry 4.0 use cases (such as the hot rolling mill). The tools (Camunda BPM server and metaphacts) and hand writing input modes used for implementing this use case turned out to be suitable candidates for further developments in similar domains.

The second use case is about the hot rolling mill plant in Eisenhüttenstadt [8]. The I2MSteel[10] project (intelligent and integrated manufacturing in steel production) has set up a comprehensive knowledge base for this kind of facility. It contains a broad model library for steel manufacturing processes including product models, process models, structure models, measurement models, order models, and storage models. This practical application scenario for the hot rolling mill in Eisenhüttenstadt combines two anomaly treatment approaches: (1) the manual (human-in-the-loop) incident reporting by using a smart pen, and (2) the automatic processing of a Semantic Sensor Network (SSN) compliant to W3C SSN Ontology [4]. The approach for pen-based incident reporting will be similar to the gas turbine use case. The automated anomaly detection

[10] I2MSteel, `https://www.cetic.be/I2MSTEEL`

relies on a collection of smart sensors that are placed in the production environment, e.g., attached to machines, products, or the production environment. All sensors are represented in a semantically modelled sensor network (SSN), which describes the sensor capabilities, their measurement processes, and typical observations. Based on a corresponding reasoning mechanism, inconsistent sensor values, broken sensors, or sensor values exceeding predefined limits are immediately detected as anomalies. These can then be integrated into the database and immediately processed at detection time. Depending on the underlying anomaly model, recovery actions can be triggered automatically.

Our extensible CPS platform suggests the integration of further input channels. Prange et al. proposed pen-based form filling using tablet computers in the medical domain [18]. It would be interesting to transfer their approach and evaluate the utility and usability in the industrial context. Further, we would like to investigate speech dialogues with gaze-based deictic reference resolution similar to [3] and combine speech with gaze-guided object classification [2] to map gaze to semantic concepts. Another promising direction is the integration of smart environmental sensors (SSN) for predictive maintenance. Multimodal multisensor input channels and corresponding recovery actions could be used to train deep networks for holistic and automatic business process modelling as suggested in [24].

Acknowledgment

This research was funded in part by the European Institute of Innovation and Technology (EIT) in the CPS for Smart Factories project, see `http://dfki.de/smartfactories/`). The responsibility for this publication lies with the authors.

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