Using Physical Factory Simulation Models for Business Process Management Research*

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Abstract The production and manufacturing industries are currently transitioning towards more autonomous and intelligent production lines within the *Fourth Industrial Revolution* (Industry 4.0). *Learning Factories* as small scale physical models of real shop floors are realistic platforms to conduct research in the smart manufacturing area without depending on expensive real world production lines or completely simulated data. In this work, we propose to use learning factories for conducting research in the context of *Business Process Management* (BPM) and *Internet of Things* (IoT) as this combination promises to be mutually beneficial for both research areas. We introduce our physical Fischertechnik factory models simulating a complex production line and three exemplary use cases of combining BPM and IoT, namely the implementation of a BPM abstraction stack on top of a learning factory, the experience-based adaptation and optimization of manufacturing processes, and the stream processing-based conformance checking of IoT-enabled processes.

Keywords: Cyber-Physical Production Systems · Factory Simulation Models · Business Process Management · Industry 4.0 · Digital Twins

1 Introduction

The production and manufacturing industries are undergoing major changes with machines, products, materials, and humans becoming increasingly interconnected via information technology to form the industrial *Internet of Things* (IoT)–a process known as Industry 4.0 [11]. Among others, these developments promise more efficient and flexible production processes, optimized supply chains,

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reduced downtimes and maintenance efforts for machines as well as cost reductions [23]. To enable the development of new concepts and prototypes in the context of Industry 4.0, openly available repositories and interfaces for accessing machine data and control functionality in real world settings are required. However, the majority of current machines and production lines are closed systems not allowing to conduct research due to high costs of downtimes and setup processes as well as safety and security concerns [18]. To remedy this situation, related work usually resorts to simulated artificial data from production environments (*Digital Twins* [5]) or to expensive high-end laboratory setups with real production machines (e. g., the *SmartFactoryKL*[4]). While the latter is infeasible for most research institutions in academic contexts, working with artificial data often does not completely reflect the actual physical properties of a production environment, especially w. r. t. runtime behavior and ad-hoc interactions with the physical world [6]. *Learning Factories* are emerging as suitable platforms for future oriented research and education [1] combining the advantages of both approaches in a *Cyber-Physical Production System* (CPPS) [18]. Being small scale physical models with a sufficient number of sensors and actuators for simulating real world industrial IoT environments, learning factories allow for flexibly conducting research on Industry 4.0 concepts and running experiments at much lower costs while maintaining the transferability of results to real smart factories.

In this paper, we present three use cases using a learning factory as physical simulation model of a CPPS to conduct research in the context of BPM. The application of concepts and technologies from the BPM domain in industrial IoT promises various advantages, among others, an easy and flexible integration and programming of hardware, events, services and humans on a process-oriented level as well as the usage of a wide range of process analysis techniques developed by the process mining community. However, apart from mutual benefits also new challenges arise with the combination of BPM and IoT [8]. With this work, we will address a subset of these challenges linked to the combination of process and event-based systems, the adaptation of processes to deal with new situations, and the application of IoT for process analysis–all in the context of smart factories.

2 The Fischertechnik Factory Simulation Model

We use a physical simulation model consisting of components developed by *Fischertechnik* (FT)[5] as testbed for research in BPM and Industry 4.0. Such physical models are referred to as *Learning Factories* [1] and used for education, training, and Industry 4.0 research (e. g., in [26,20,9]) enabling the development and evaluation of research artifacts in a protected environment before moving to real world production scenarios. The custom factory model we use[6] simulates a complete production line at low costs (<15,000 EUR) consisting of two shop floors that are linked for the exchange of workpieces as shown in Fig. 1. Each shop

[4] https://smartfactory.de/
[5] https://www.fischertechnik.de/en/simulating/industry-4-0
[6] https://iot.uni-trier.de

floor consists of 5 identical machines: a sorting machine with color detection, a multi-processing station with an oven and a milling machine connected by a workstation transport, a high-bay warehouse, and a vacuum gripper robot. Additionally, the first floor has a punching machine and a human workstation and the second floor a drilling machine including stations for pickup and delivery. Each shop floor is equipped with 13 light barriers, 16 switches, and 3 capacitative sensors for control of the actuators comprising 16 motors, 4 compressors, and 8 valves. The machines are enhanced with sensors mounted on moving parts, motors, and compressors for condition and pressure monitoring for predictive maintenance [9]. Moreover, RFID and NFC readers/writers are integrated into the stations resulting in 28 communication points. This allows each workpiece to be tracked and required manufacturing operations and parameters to be retrieved and adjusted during production. Furthermore, a camera is placed above the two shop floors to track the workpieces. An additional environmental sensor provides climate data (e. g., room temperature, humidity, illuminance, air pressure). The workpieces used for simulating the production are small cylindric blocks (height = $\sim$1.4 cm, diameter = $\sim$2.6 cm) of varying colors each equipped with an NFC tag, which contains information regarding the individual workpiece such as an identifier, the type (i. e., color), the current production state, and timestamped production history. The sensors and actuators of the processing stations are connected to Fischertechnik TXT controllers; 6 Raspberry PIs and 2 Arduinos are used for managing the additional sensors and the camera, which are all linked via Ethernet to a central network switch. The embedded controllers run C/C++ or Python code to control the sensors and actuators. An integrated MQTT server publishes high-level factory data (e. g., machine states, order and production states, environment and NFC readings). An external Apache Kafka server provides more fine grained access to sensor data.

3 Related Work

Physical factory models are increasingly used to carry out Industry 4.0 research and for education purposes. Primarily, two types of research environments can be distinguished: small scale physical simulation models and full scale physical production lines. The *SmartFactoryKL* and the *LPS* learning factory [20] at the University of Bochum are examples of full scale physical manufacturing environments that are used for research and education. The learning factory *AutFab* of the University of Applied Sciences Darmstadt [26] is another example for using real production machines in this context. Disadvantages of these kinds of production line setups are that basic experimental research is much more difficult and expensive to carry out, since it requires profound knowledge about the machines; the costs for acquisition, networking, maintenance, equipment, and operation are high; and the simulation of errors is difficult and could lead to high costs if the machines are damaged in this process. Therefore, small scale physical factory simulation models are increasingly gaining attention in research and education

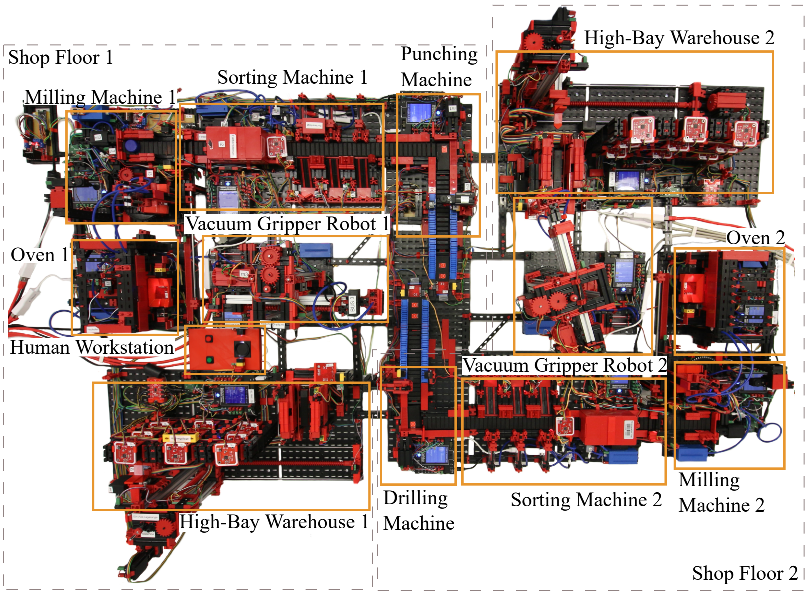

Fig. 1. The Physical Factory Simulation Model.

as alternatives, e. g., the *DBISFactory* at the University of Ulm[7], the Lego factory at the University of Vienna[8], or the DFKI-Smart-Lego-Factory [21], all of which are also partially used for conducting BPM research. In contrast to relying on completely simulated data, these types of simulation models provide much more realistic data and behavior, especially in a highly dynamic CPPS.

Related research addresses the application of BPM in smart environments such as smart logistics [2,16], smart health [7] and emergency management [14], smart homes [25] as well as smart factories [24,28,13,15]. The work by Mangler et al. presents a general discussion of applying BPM technologies in the context of Industry 4.0 [13]. An approach for IoT-aware process execution of industrial maintenance processes is presented by Schönig et al. in [24]. They propose an architecture to integrate IoT data into business processes to determine how and when certain work steps should be carried out by production workers. Baumgraß et al. present an architecture for event-driven process execution and monitoring in smart logistics [2]. This is complemented by work of Meroni et al. showing an artifact-driven approach to monitor business processes through real-world objects [16]. Marrella et al. present the *SmartPM* system in [14], which is able to detect deviations between physical and virtual environments during process execution and resolve them using automated planning techniques. The system is motivated by emergency management scenarios with structured processes and corresponding ad-hoc exceptions. The *PROtEUS* system follows similar goals

[7] https://www.uni-ulm.de/in/iui-dbis/forschung/laufende-projekte/dbisfactory/
[8] https://wst.cs.univie.ac.at/research/projects/project/292/

and approaches for enabling self-healing of processes in the smart home domain [25]. Wieland et al. discuss an approach for using situation-aware adaptive workflows in the manufacturing domain with a corresponding Workflow Management System (WfMS) called *SitOPT* [28]. In addition to the normal workflow model, situational workflow fragments are constructed that define which actions should be performed in certain real world contexts to adapt the process.

Only a few related approaches discuss the integration of BPM and IoT in the context of Industry 4.0. These works propose new concepts without providing comprehensive evaluations, especially not based on real world experiments (e. g., [28,15,13,14]). If evaluations are conducted, mostly simulated data from IoT is used, presumably due to high costs and effort w. r. t. hardware, setup, and maintenance for running real world experiments in production environments. At this point, learning factories may help to mitigate some of these issues and facilitate research in the Industry 4.0 domain. Our research is based on real world data obtained from interactions with the physical world via the physical simulation models introduced in Sect. 2. These make it possible to identify and discuss more realistic problems associated with the challenges presented in the BPM-IoT Manifesto [8]. Furthermore, our work puts more focus on industrial processes and their intelligent automation from a BPM point of view.

4 Use Cases for BPM-IoT Research

In this section, we describe three use cases for research in BPM based on physical factory simulation models that we are currently investigating. The presented custom FT factory model thereby serves as testbed for research while the research questions and new concepts are targeted to be more generic and also applicable to other factory configurations and IoT settings.

4.1 Implementation of a Business Process Abstraction Stack

Problem Statement: Many complex IoT environments–including the FT factory described in Sect. 2–consist of a multitude of sensors, actuators, and computing units. These components are usually programmed in low-level languages and controlled by software close to the hardware with code (e. g., G code or C code) running on embedded controllers (e. g., Programming Logic Controllers (PLC) in industry), which limits flexibility and interoperability of components to create more complex processes [18]. As with the FT factory only a few static processes are "hardwired" in C code to demonstrate the functionality. Remote access and a flexible composition of functionality into new (business) processes or to adapt existing ones is not possible. An additional software stack is required on top of the existing IoT components to raise the programming and research to the abstraction level of business processes supported by a WfMS and with that to exploit the potential of integrating BPM with IoT [8].
Research Challenges: Enabling the programming of a smart factory on the level of business processes involves the selection of suitable hardware components

(sensors/actuators) to detect events relevant for the process execution, e. g., to monitor the production steps, workpieces, stock, and resources (*C1*: Placing Sensors in a Process-aware Way [8]). It also requires the investigation of the micro-processes at the individual machines and stations as well as their interconnections to achieve an efficient and flexible production line (*C6*: Managing the Link between Micro-Processes [8]). This also means that static and coarse grained "hardwired" processes have to be relaxed and detailed to achieve a more flexible composition of smaller processes (*C7*: Breaking Down End-to-End Processes [8]). The FT factory is a perfect example of a complex IoT system, which is both event-driven due to large amount of sensors and process-based (*C13*: Bridging the Gap between Event-based and Process-based Systems [8]).

Approach: With the configuration of the FT factory described in Sect. 2, we invested a significant amount of work to create a comprehensive and realistic simulated production line with partial redundancy regarding machines as well as a large number of sensors to monitor production stages, workpieces, machines, and the environment. Fig. 2 shows our approach of introducing additional software layers to conduct BPM research using the factory. The individual hardware components are controlled by software written in a low-level programming language running on embedded controllers. We analyzed the data and functionality of these devices, refined, grouped, and abstracted them from an Object-Oriented Programming (OOP) point of view to create software components in an OOP library that can be used for developing more complex programs in higher level OOP languages. An excerpt of a machine class and the general controller interface including relevant attributes and methods can be found in Fig. 2. Furthermore, we added a web service layer on top of this OOP layer to make the functionality (i. e., the machines' methods) and data remotely accessible in a service-oriented (RESTful) architecture and via messaging systems such as Apache Kafka. The developed web services were semantically enriched and integrated into the domain ontology FTOnto [12], which contains formal manufacturing knowledge tailored to the FT factory [10]. These web services are the basis for implementing business processes on top of the factory to model, enact, and monitor processes with the help of a WfMS such as Camunda[9] and thereby enabling us to conduct BPM research in the context of Industry 4.0.

Example: An example for the business process-oriented abstraction is the implementation of the mill functionality of a milling machine in the FT factory. This machine consists of multiple actuators and sensors that have to be activated in low-level function calls to the individual actuators (e. g., for the transport to and from the machine). We abstracted these calls into a sub-routine, which is now available as the *mill* method on the OOP layer and exposed via a service on the Web Service layer. A *Service Task* modeled in BPMN 2.0 and executed by the WfMS can be used to invoke this *mill* method via a web service.

Discussion: One of the most fundamental research activities associated with creating such an abstraction stack is analyzing the functionality of available sensors and actuators and grouping and abstracting them at a BPM-oriented

[9] https://camunda.com/

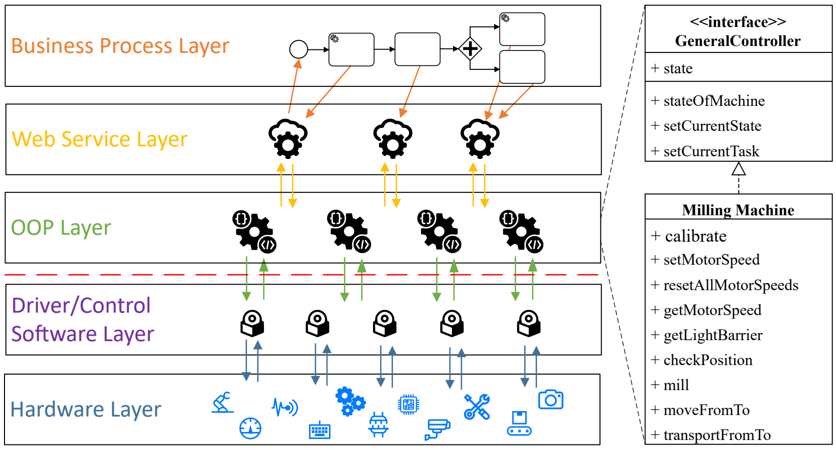

Fig. 2. Hardware and Software Layers for BPM Research on Learning Factories.

level *(C1, C13)*. As there is no generalizable approach for IoT environments here, this process of abstraction should be done based on the actual requirements of the users and domain considering trade-offs between high flexibility of processes with a very fine grained abstraction level and loosing flexibility and expressiveness by being more coarse grained *(C6, C7)*. In the first case, modeling and configuration of the individual processes requires higher efforts, in the latter case, process modeling and implementation is simpler. The degree to which the proposed software stack can be applied in real production environments has to be further investigated as the hardware components of the factory (e. g., the embedded FT controllers as simplified PLCs) are only partially suitable for industrial use and may not fulfill safety and security related requirements.

4.2 Experience-based Adaptation and Optimization of Processes

Problem Statement: Production processes are often implemented in a rigid manner lacking the flexibility to adapt to dynamic situations such as changed customer demands and individualization or machine breakdowns [11]. When processes cannot be executed as previously planned, constant re-planning and optimization is required [22]. The integration of sensors and other IoT resources in production environments opens new opportunities for process adaptations but it needs to be investigated to what extent this data can be used for production planning and adaptation as well as optimization of processes in real time.
Research Challenges: IoT-aware processes are highly context-sensitive and IoT environments unstructured and dynamic (*C5*: Dealing with Unstructured Environments [8]). New situations can emerge in an ad-hoc manner that lead to unanticipated exceptions during process execution requiring the currently executed process instance to be adapted to the new context (*C12*: Dealing with New Situations [8]). Furthermore, adaptations can also affect other process in-

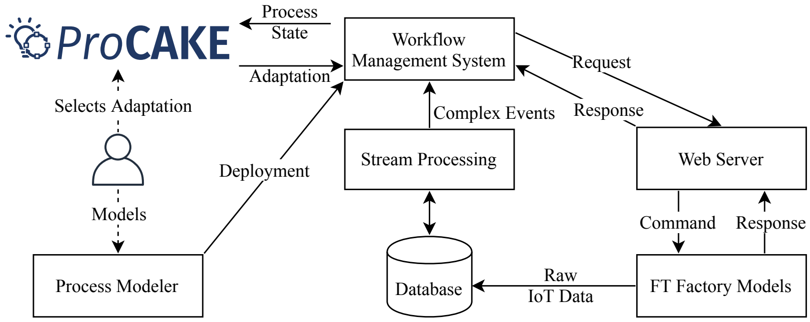

Fig. 3. Architecture of the Integration of ProCAKE with a WfMS.

stances that may then have to be changed, too. Regarding IoT resources, several autonomy levels exist from full supervision by a central unit to complete independence of central control (cf. *Edge Computing* [7]). Thus, it must be decided what autonomy level the individual resources in the FT factory should have, e. g., if micro-processes of a machine can be performed independently of supervised control by a central unit (*C9*: Specifying the Autonomy Level of Things [8]).

Approach: For adaptation and optimization of manufacturing processes, we investigate the use of Artificial Intelligence (AI) by combining widely used planning techniques [22,15] with other experience-based learning methods. By combining these methods, we expect a reduction of the computational and knowledge acquisition efforts that are often very high for planning-based approaches due to their use of comprehensive real world domain models (full observability assumption). Process-oriented Case-based Reasoning (POCBR) [4,17] is examined as an experience-based learning method that deals with the reuse of procedural experiential knowledge. We use the Camunda WfMS in combination with the *Process-oriented Case-based Knowledge Engine* (ProCAKE) [3], a system that is tailored for developing POCBR applications (cf. Fig. 3). Production processes can be modeled in BPMN 2.0 (see Sect. 4.1) using Camunda Modeler. During execution of a process instance, the service tasks invoke the corresponding web services that are semantically enriched to allow for verification of preconditions before the activity is performed. ProCAKE detects state changes of the process and adapts it according to the currently available resources and other executed instances if necessary. Here, users can choose in an interactive way from several adaptation options. The adapted process instances are sent back to Camunda and continued. If several process instances require the same adaptations repeatedly, a migration to an evolved process schema may be necessary. To determine the successful execution or failure of activities, the Complex Event Processing (CEP) platform Siddhi[10] is used, which processes IoT data from Apache Kafka and deduces higher level events for the executed activities (cf. Sect. 4.3).

[10] https://siddhi.io/

Example: An example scenario could be a malfunction of the drilling machine, which can be determined via sensors and inferred from the FTOnto domain ontology [10]. As only one drilling machine is available in the two shop floors, a process adaptation must be found. ProCAKE determines via the ontology that one of the two milling machines could also be used to drill a hole due to the semantic equivalence of the provided operations, which would also be chosen as an alternative by a production worker. Another option may be that other activities are executed first and the affected process step is relocated to a later stage. In these cases, further process steps must be changed to transport the workpiece to the respective machine. Other examples for this use case include the resource-optimized allocation of orders to the individual machines to achieve a specified goal such as energy, time, or cost optimization.
Discussion: How to capture and formalize the knowledge of production workers and their unstructured environment is one of the fundamental challenges to be addressed *(C5)*. Using past successful process executions to learn possible adaptations of process instances automatically to deal with new or similar already experienced situations *(C12)* seems to be promising [19]. In general, the integration of humans both in the production process itself and in the application of AI-based methods is challenging, e. g., explanations of automatically executed adaptations should be meaningful and transparent for users. Another research question is about the adaptation of simultaneously executed processes within the factory. Production processes may concurrently access the same physical resources and are interrelated among each other. Thus, it is necessary that adaptations of one process instance do not have negative effects on other processes or that users are aware of these impacts. A fundamental technical question in the FT factory is finding the right level of autonomy of IoT devices, which are often resource constrained and therefore not capable of exhaustive computations. The calculation of possible adaptations is rather complex and in addition to the execution of control commands not always feasible on such devices *(C9)*.

4.3 Stream Processing-based Conformance Checking

Problem Statement: A WfMS may not always exist for monitoring and controlling processes and individual activities. In addition, the implementation of a BPM stack as described in Sect. 4.1 may not be feasible or possible due to high costs and closed hardware/software interfaces of the individual devices. Thus, third party engineers and machine setup workers have no influence on data produced and interfaces provided to program the machines at a BPM-oriented level. However, production processes, machines, and various quality-related aspects still have to be monitored and checked to guarantee the correct execution of processes, also at a BPM level (cf. *Conformance Checking* [27]).
Research Challenges: Here, we investigate ways of integrating IoT sensor data, CEP, and BPM technologies for analysis of process execution (*C3*: Connection of Analytical Processes with IoT; *C13* [8]) even in settings without a WfMS monitoring the execution of processes and activities. The data from IoT sensors is used to check the conformance of process executions (*C4*: Integrating

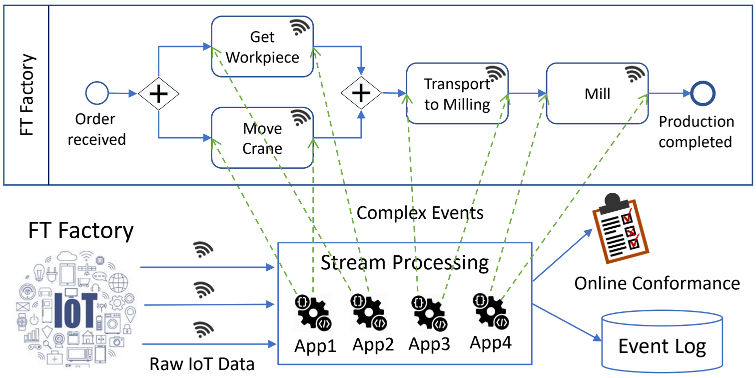

Fig. 4. Architecture of the Envisioned Conformance Checking System.

IoT into the Correctness Check of Processes [8]) both in offline settings and also at runtime (*C14*: Improving Online Conformance Checking [8]).

Approach: Specific patterns and combinations of IoT data can be used to identify the start, stop, progress, and various other aspects and key performance indicators related to the execution of business processes and activities. Despite the absence of a WfMS for the standard configuration of the FT factory, we are still able to identify the production processes at a BPM level–either based on knowledge or on observations about the individual processes–and to model the processes including activities, gateways, events, messages, resources, etc. The activities can then be enriched by domain experts with IoT related event patterns/queries that are used to detect execution related aspects (e. g., the start and the successful completion of an activity). We use the Camunda WfMS to model the production processes in BPMN 2.0 and associate Siddhi apps with the individual activities. The CEP platform Siddhi is connected to the specified IoT data sources and used for deriving higher level activity-related events based on the event queries within the Siddhi apps. That way, the execution of individual process and activity instances can be monitored and checked for conformance in an online setting but also used for complementing process event logs.

Example: Fig. 4 shows the envisioned architecture of the conformance checking system and its correlation with an example process from the FT factory. Each activity is associated with a dedicated event processing app running on the stream processing platform (here: Siddhi), which is connected to the FT factory's sensors via Kafka and/or MQTT. The apps contain one or multiple queries that link sensor data from the factory using logical operators, mathematical functions, aggregations, filters, time-based operations, etc. to identify the start and end of an activity. Based on the raw IoT data (e. g., from light barriers, NFC/RFID readers, production machines, cameras) and the queries defined in the apps, complex events related to the execution of the process are derived, which are then added to the process event log for the executed case or used to provide direct feedback about conformance of the process instance.

Discussion: Among the more fundamental questions of correlating IoT data with process executions is finding the appropriate sensors, algorithms, and domain knowledge to create the correlation patterns, especially regarding activity detection *(C3, C4, C13)*. Available sensors may not provide sufficient information to clearly identify activity executions resulting in uncertainties that need to be dealt with during log creation and to enable conformance checking *(C14)* by looking at the larger process context (e. g., previously executed steps). Also the correlation of a detected activity to a specific process instance is challenging in such a complex IoT environment with multiple instances running in parallel. We expect this correlation of IoT data with process executions to be complementary to existing techniques for (online) conformance checking and used for enriching process event logs with aspects that can be measured through IoT.

5 Conclusion and Future Work

We presented our physical Fischertechnik factory simulation model as testbed for conducting research in the context of Industry 4.0 based on the combination of BPM and IoT. We introduced three exemplary generic research topics that we are currently investigating: 1) the implementation of a business process abstraction stack on top of the factory simulation model; 2) the experience-based adaptation and optimization of manufacturing processes; and 3) the stream processing-based conformance checking of IoT-based processes. By using physical factory models as testbeds for evaluations, research is more realistic–but also more challenging–than using artificial data in this kind of highly dynamic CPPS. The physical factory models enable the validation and demonstration of developed research artifacts in a protected environment. At the same time, this close-to-reality simulation of a real production line facilitates the transfer of developed concepts into practice. In future work, we will further investigate the more fundamental research questions associated with the use cases and implement them. We will also examine how the developed research artifacts can be applied to and evaluated in large scale simulation models and real world shop floors.

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