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Process Automation and Process Mining in Manufacturing

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Abstract. Process automation and process mining are (interconnected) key technologies with respect to digital transformation. Hence, expectations are high, in particular, in challenging application domains such as manufacturing that combine systems, machines, sensors, and users. Moreover, manufacturing processes operate at a high level of collaboration, e.g. in inter-factory or cross-organizational settings. This paper investigates the following questions: 1) How to automate manufacturing processes? 2) What are the specifics with respect to the involvements of humans? 3) How do the automation strategies impact process mining options and vice versa? For 1), we discuss two starting positions in practice, i.e., legacy automation and greenfield automation. For 2), we discuss the range of automation options with respect to human involvement, i.e., non-interactive automation, robotic process automation, supportive process automation, and interactive process automation. For 3), the different automation settings and strategies are examined with respect to data collection and integration capabilities. Conversely, process mining is discussed as technology to further process automation in manufacturing. The paper builds on more than a decade of experience with process automation in manufacturing. We built an orchestration engine based on which 16 real-world manufacturing processes have been realized so far, resulting in various benefits for the companies such as traceability, flexibility, and sustainability. The investigation of the manufacturing domain also sheds light on other challenging scenarios with similar requirements such as health care and logistics.

Keywords: Process Automation, Process Mining, Manufacturing, Human Aspect, Data Collection and Preparation

1 Introduction

Process automation and process mining are regarded as key technologies for digital transformation [6]. Process mining provides the required transparency for digital transformation and can complement process automation [14]. In this work, we discuss these prospects for a challenging domain, i.e., manufacturing. Manufacturing is challenging–and one of the most interesting domains for

Business Process Management–as it *"combines high demands on process transparency and digital transformation and it combines the physical world (e.g., sensors, machines), human work, and manufacturing systems"* [18]. As such the manufacturing domain, poses high demands on *integration*, i.e., vertical integration across the automation pyramid [11] and horizontal integration of multiple entities and partners, e.g., inter-factory or cross-organizational settings [16].

This paper investigates the following questions:

1. *How to automate manufacturing processes?* We discuss two starting positions that are prevalent in practice, i.e., legacy automation–starting with existing hardware and software–and greenfield automation, i.e., at least for the software part being able to start from scratch. For both starting positions, guidelines based on experience from different automation projects are provided.
2. *What are the specifics of process automation with respect to the inclusion of (human) users?* This point is crucial as *"smart data, insights, and transparency will be useless if the process experts or process owners do not appreciate and support the approach"* [14]. A range of automation options exist that have different impact on the involvement of humans, i.e., non-interactive automation, robotic process automation [1], supportive process automation, and interactive process automation [8]. We illustrate the different options with real-world scenarios.
3. *How do process automation strategies impact process mining options and vice versa?* Process automation and process mining are perceived as being intertwined. The different automation settings and strategies are examined with respect to data collection and integration capabilities. Conversely, process mining is discussed as technology to further process automation in manufacturing. We will report on our experiences from process mining projects in manufacturing where the expectations are high, but especially for small and medium sized enterprises the infrastructure poses a critical challenge [19]. Manufacturing offers opportunities for process mining as an abundance of data is available, for example, process event data[1] plus sensor data in form of time series [20] and engineering drawings [15].

The paper builds on more than a decade of experience with process automation and mining in manufacturing. We built the manufacturing orchestration engine `centurio.work` [11]. It is based on open source process execution engine CPEE[2] [10] which is employed worldwide and has been downloaded 500.000 times[3] by today plus an additional 23.000 downloads[2] for manufacturing specific add-ons, e.g., for connecting machines using standard format OPC-UA[4]. 16 process scenarios at 7 manufacturing companies run or are currently in various stages of

[1] stored in process event logs (*logs* for short in the following.)
[2] `https://cpee.org`
[3] `https://rubygems.org/profiles/eTM`, last accessed on 2021-07-02
[4] `https://opcfoundation.org/about/opc-technologies/opc-ua/`

realization based on centurio.work. This results in various benefits for the companies such as traceability, flexibility, and sustainability. The investigation of the manufacturing domain also sheds light on other challenging scenarios with similar requirements such as health care and logistics.

The remainder of the paper is structured as follows: Section 2 starts with legacy process automation and contrasts it with subsequent greenfield process automation (↦ Question 1). Section 3 picks up the human aspect as key factor in digital transformation projects and examines different automation settings along their inclusion of humans (↦ Question 2). Section 4 sheds light on the intertwining of process mining and automation in manufacturing (↦ Question 3). In Sect. 5, we discuss the findings and provide an outlook on future topics.

2 Automating Legacy vs. Automating Greenfield Scenarios in Manufacturing

The automation of legacy and greenfield scenarios constitute two “extremes” on a range of possible starting points in manufacturing and other domains. Starting points in between, i.e., with “mixed” circumstances, are common. Hence, often the techniques and circumstances elaborated below have to be considered.

2.1 Automating Legacy Scenarios

Legacy scenarios suffer from the constraint that pre-existing hardware and software has to be reused, and that environmental constraints potentially limit how the processes are carried out. The proximity of physical machines, for example, might influence the optimal order of tasks or interactions with humans.

We assume that processes exist, although in a non-formalized choreography between humans, software, machines and the environment. These processes

- are not fully understood by individual human actors, i.e., process participants.
- are not fully structured. They include a large amount of leeway regarding the order of steps and exception handling. Common sub-processes shared between different parts of the processes are often not perceived as such.

What we will not find in the real-world are logs alongside the execution of these processes. Consequently, at this point, there is no chance that process mining can be applied to discover the process model for process automation. In fact, machines log data into individual data tanks without any notion of different produced parts, or differentiation of when they produce parts or when they are just idle. Heterogeneous software components of varied age typically also keep their own logs, with no notion of orders, customers, or parts.

So unless the whole factory floor–order management, production, packing and delivery including humans, software, machines, and environmental involvement–has to be mapped into a single big process (which will most probably not yield any useful results), it is imperative that an initial notion of how things work is established. This has to be done by domain experts. Only then can the properties according to which the logs have to be split, be understood and techniques like process mining can yield useful results. A remaining question is whether process elicitation (e.g., by interviewing domain experts) is done beforehand. In any case, corresponding techniques can be used to check the progress in formalizing domain knowledge.

Roughly knowing the processes is a first step. The iterative evolution from passive observation of the scenario to actively controlling the interaction between humans, software, machines and the environment [11] is a much more complex endeavour. The following questions can be used to plan for this evolution:

1. *Hardware read capabilities:* Which event data streams can be read during operation (reading state/configuration is considered a command)? Do we need additional sensors (e.g., temperature, vibration) for meaningful data analysis?
2. *Hardware command capabilities:* What is the granularity of the digital interface, i.e., component level such as individual motor control vs. operation control? How and when are humans involved?
3. *Humans:* What are the observable points in time where it is exactly known that a human starts something, or ends something?
4. *Software:* How to access static data, observe data changes, track operations? Is it possible to observe how humans interact with the software?

1. Hardware read capabilities: Machines should be observable during operation. If a machine cannot provide data about its operational state, and parameter changes during operation, it has to be replaced or updated with suitable capabilities. All future data analysis to improve the process depends on data. In addition, supplementary sensors can be added around or inside the machine with separate interfaces that are not crucial for production, but add context to it.
2. Hardware command capabilities have to be seen strictly separate from the read capabilities. While the readable interface yields data streams, and can be used to passively monitoring the machine, hardware command is about active automation. Machines often expose fine granular commands such as switch on/off individual parts, start individual motors or auxiliary systems, or execute NC (numerical control) programs. Many of these individual steps might be performed by humans in certain sequence all the time. So it is imperative to identify when a human is really required / desirable, and what are sequences that can be bundled together as static sub/processes to be reused over and over again.
3. Humans: Their tasks often represent the **digital gap**. It is important to split their work into individually/automatically observable units. This often requires additional sensors, or additional effort by the humans to tell an information system what they are actually doing right now. It is imperative for the well-being of humans, that tracking is as passive as possible. Being required to do reporting in addition to the actual work can lead to frustration and errors, and humans have a tendency to minimize such tasks, cmp. (health) care [17].

4. Software: Finally integrating legacy software systems is often the most challenging part, because their complexity is often much higher and they are much more of a black box than any involved hardware or human. The following aspects should be analysed in roughly this given order:

- Does the software expose a comprehensive network accessible interface? In this case everything is fine. Even if legacy protocols are used, it is simple wrap the software into a service to provide for full automation capability.
- Does the software expose a local API? In this case again a network accessible wrapper service can solve the automation problem.
- Does the software utilize a database? Is it possible to infer operations or human interactions from data changes? This requires additional analytical steps, e.g., building differential snapshots [7].
- Does the software expose a UI? If none of the above ways of interacting with the software can be utilized, techniques such as Robot Process Automation (RPA) can be employed. Few approaches have considered RPA in manufacturing-related scenarios yet. [21] look at RPA for automotive, but focus on ordering and reporting processes rather than on lower-level production processes. In one of our projects, RPA was used with some hardware, e.g., a rubber finger pressing a button. RPA for manufacturing processes is further discussed from the human perspective in Sect. 3.

If the software does expose logs, they can be utilized to create a (run-time) event stream. Of course it has to be determined what the latency between operation and logging is to judge the usefulness for automation.

Approaches such as RPA, although not circumventable for some legacy scenarios, should be avoid whenever possible as they (1) tend to subtly break with small changes to UIs, (2) can/should never be reused for inevitable replacements of legacy software. Modern software typically encompasses the long-taught principle of software development to separate UI, business logic, and data. Accessing data is typically exposed through well-defined, network-accessible APIs (accompanying UIs–web, mobile, desktop–and custom extensions typically are separated from the core and also access data through these interfaces).

2.2 Automating Greenfield Scenarios

Regarding the utilization of machines and humans, greenfield automation projects are no different from legacy projects.

When selecting or developing software, for integration with process aware information systems, the following guiding principles have proven useful:

- *Always separate the business logic:* Process management/orchestration engines are a means to separate the application/business logic from functions. Individual software include no hard-coded or configured assumptions about the environment or how to interact with peers (e.g., protocol or addressing). Loosely coupled systems are easier to maintain, debug, and evolve for future yet unknown scenarios.

- *Modularization:* Evolving and adapting your system to ever-changing business conditions works best when you have small self-contained services, that expose functionality or data. Changes to the functionality itself should be as localized as possible. It is easier to maintain small and overseeable pieces of software than bit and complex pieces. Localizing errors is easier when functionalities are clearly separated as services.
- *Avoid central databases:* Services should each have their own data storage when possible. Software often breaks when data structures are changed and different functionalities sharing these data structures have to be adapted to realize the change. All data should be passed between services through the service interfaces if possible. This greatly reduces coupling and allows of localized changes. Compatibility can be ensured and made transparent through separated transformation (e.g., additional steps in a process models or service chains).
- *Focus on Observability:* Process automation is about orchestrating services and their interaction. Maximizing the information accompanying each interaction between services makes it easier to conduct the necessary analysis steps for process improvement. Observability includes data streams about system health (e.g., resource utilization), exceptions, metrics (e.g., performance or inner state), and auditing (e.g., information focused on checking sanity/compliance of involvement in business logic).

3 The Human Aspect in Process Automation

Humans have many roles, even in fully automated scenarios. In general, humans are involved in running processes in the following two capacities: they are either *process observers* or *process actors*.

Process observers are monitoring the execution of processes, but they not actively participate in them. They typically do passive tasks such as error detection, compliance checking, quality checking, or safety monitoring. The tasks of process observers are the same, whether a process is fully automated or fully manual. Collecting information and enacting the consequences, of course, may be different in fully automated vs. fully manual scenarios. Process observers typically enact the following consequence action: *"stop the process"* based on observed anomalies or violations. It is then up to process actors to fix things.

Process actors again might exist in fully automated and manual manufacturing scenarios: periodic as well as problem-related maintenance, for example, is always connected to human interaction. Process actors might exist in two roles:

- *Active* process actors hold business logic and exert control over the process by actively directing it, e.g., by selecting the machines that produce something, or selecting the next steps.
- *Passive* process actors which only act within well defined constraints. They are basically not distinguishable from software, as from the point of view of a process orchestration engine they behave the same: (1) they get a well-defined set of instructions/parameters and (2) they return a well-defined

data-structure that represents the computer-readable result of the instructions. Humans involved in a fully automated scenario through a worklist [13] are such an example.

Thus a fully automated scenario is not characterized by the non-involvement of humans, but instead by the formalization and automatic observability of all interactions between humans, machines, software and the environment.

Figure 1 depicts a range of scenarios with focus on the human involvement as well as techniques that are typically used to solve the challenges imposed by the scenario.

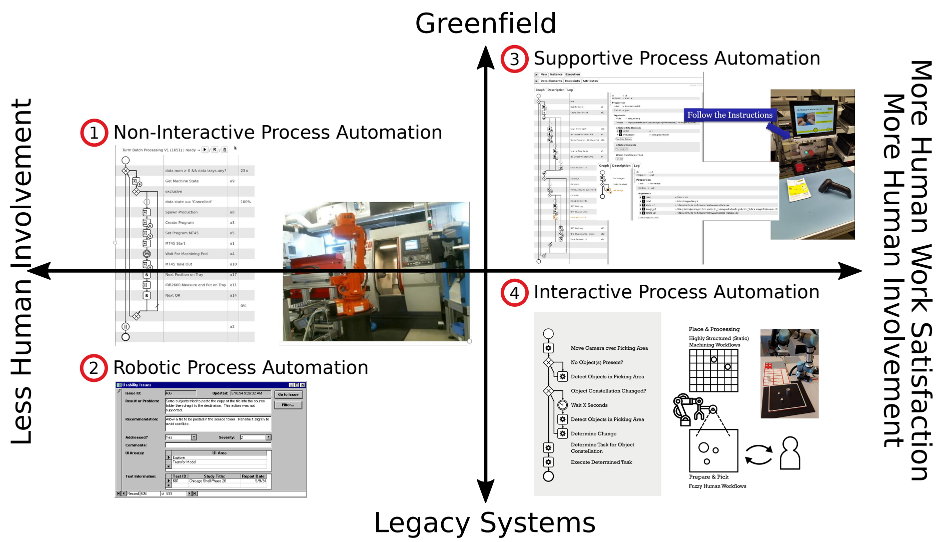

Fig. 1. Manufacturing Process Scenarios and the Involvement of Humans

The X axis denotes the requirement for the involvement of process actors. Many scenarios in manufacturing, health care, or any other domain are currently neither feasible nor efficient to be carried out without humans. The Y axis picks up the two starting positions discussed in Sect. 2, i.e., to evolve scenarios which include legacy systems into into fully automated scenarios and to design and realize everything from the ground up (greenfield).

Scenario (1), further detailed in [12], describes the automation of a mixture of legacy machines and additional hardware. The purpose of the automation was, to do away with all human interaction and allow for fully automatic production of batches. The following machines are involved: a turning machine, that produces the part, a bar loader that feeds parts to the turning machine, a robot that extracts the parts, puts them into a "close-to-production" measuring machine and then puts them onto an autonomous guided vehicle (AGV). The AGV drives a full load (60 pieces) to a tactile coordinate-measuring machine (CMM), where a robot puts each piece into the CMM, and extracts them again, after the measurement finishes. When a batch is ready the AGV drives the batch to packaging, and then goes back to get new parts. This fairly involves humans purely as process observers, that check quality deviations, and if they are too big, signal production stop. Then human actors change tools (them being blunt–depending on temperature and type of part produced–being a main source of error).

Before the full automation humans were starting the machine manually (a repetitive task), and also taking manual measurements "close-to-production". While starting the machine manually required a skilled worker to be present at all time, after automation the worker could do more useful things like planning the production of future parts. The manual measurement was another major source of errors, mainly because the measurement was documented by hand, an was handed over the person in charge pf the CMM. Predictably enough the notes were not always clear, and lots of time was wasted measuring parts with the CMM which were clearly faulty to start with. After automation no more humans were involved.

For Scenario (2), legacy software, which only has a user interface, has to be brought into a non-interactive process automation. In this particular case, a partner company wanted to extract information from an order management system on an IBM iSeries (AS400). Because the whole system had been outsourced under a certain contract, it was not possible to access the information directly in the database. Instead operators were manually using a UI to copy the information between systems. By using RPA techniques, it was possible to select the correct order, and extract the order information. The order information was differently structured on screen for different products. It also was in a different and sometimes faulty format compared with the format needed in the second system: before introducing RPA that format had been graciously translated by the operators in their head, including assumptions about faulty entries. So besides extracting the information through RPA, even bigger effort went into interpreting to data to be valid input for the second system. From the point-of-view of the process engine utilized in the project, RPA was just one task (extract information). Additional tasks and decisions dealt with transforming data to be valid input for the final task (print production label and QR code). In this scenario, the process actors have been replaced and RPA was a necessity due a legacy system. The inevitable replacement of the legacy system will lead to the replacement of the RPA task, with a simple "read order data" task that gets the information from a database or through a microservice interface.

Scenario (3) is a worker-assistance scenario, which we currently automate together with a company partner. Worker assistance is typically deployed due to the following reasons and properties of a scenario:

- The scenario is complex with lots of variants and special cases. The actual scenario deals with the assembly of highly customizable parts which are a mix of mechanical and electronic parts with a custom firmware. The number of mechanical variations exceeds 20000. This number multiplies when custom firmware flashing and configuration is taken into account.

– Due to the many variants and the tedious assembly process, automation with robots or machines is not feasible.
– Humans involved in the production process have different skill levels, and have to be supported with different levels of information.

In this particular scenario, the goal was to introduce a production line with fine-grained labor division. While before automation, the parts where assembled by two humans, after automation, eight people are to be involved. The production line thus consists of eight working stations. The parts are autonomously transported between the working stations. The purpose of the worker assistance system is to identify the part present in a working station, identify the human present in a working station, and display information tailored for a specific variant AND the skill level of the worker.

While experienced workers can be slowed down by detailed information (individual steps have to be acknowledged to provide insight into assembly timing thus error sources), less skilled workers greatly benefit from looking up information in a multitude of binders, being presented with all relevant information.

Work satisfaction in this scenario greatly increased, as well as overall productiveness. At the same time faulty parts due to faulty assembly could be reduced. Through fine-grained monitoring of human assembly also bottlenecks could be detected, as well as faulty raw-materials could be identified faster due to integrated reporting capabilities. All interactions between humans, the production line, and additional hardware was realized through micro-services [9], and orchestrated with a process engine.

Scenario 4, further detailed in [8], describes how at the beginning or the end of a non-interactive process automation humans might interact with machines, here through a loading station. A loading station enacts a pick-and-place scenario, where humans put tools or raw materials on designated area, in no particular order, position or rotation. A robot then visually detects, selects, orders and consistently places the provided objects (with high precision, no deviations from position) for further processing. Humans are exonerated in that the rules are simplified - they interact just like with fellow humans; they provide parts. From the point of view of automation this is also a simplification. After the loading station deterministic behaviour prevails, that can be solved by simple logic instead of focusing on variations throughout the automation. Loading stations can hence be a simple solution for interfaces between humans and legacy production lines.

4 Process Mining and Automation: are they Twins?

The discussion of automation scenarios in Sections 2 and 3 indicates that process automation and mining are intertwined in the following ways:

1. Process mining can support automation. The precondition is the existence of suitable data.

2. Process automation can yield integrated and contextualized data collections [11] and hence lead to increased quality of process mining results and unlock novel ways of analyzing the data [20].

The collection of process event logs as input for process mining is a critical and tedious task. One of the conclusions from the focus group interviews with manufacturing experts presented in [19] is that, particularly for small and medium sized manufacturing enterprises, *"logging is part of the business logic and data-centric. Selected milestones in the production produce a data dump with a timestamp, while most process steps in the manufacturing domain just produce no events at all"*. If there is no (process-oriented) integration across the levels of the automation pyramid already in place, the log data can possibly accessed "per level", i.e., from top to bottom, the Enterprise Resource Planning (ERP) system level, the Plant Management level, the Process Control level, and the Control (PLC) level [11]. The log data possibly accessible at the different levels varies in quality with respect to the L^* quality model proposed for process mining [2], ranging from *** (events are automatically recorded, but unsystematically, some correctness guarantees can be assumed) for the ERP level to ** (events are automatically recorded, but unsystematically, no correctness guarantees exist, leading to e.g., missing events) for the other levels. There are (commercial) connectors/adaptors for process mining on ERP data, e.g., for open source platform ProM [4] and Celonis for SAP©[5]. However, in addition to the probably low data quality, there is no interconnection between the systems, resulting in isolated analysis results.

Hence, process automation with its strong integration aspect can immediately lift up the quality level to at least a quality of ****, i.e., the data is recorded in an automatic, systematic, and reliable way, and the contextualization in processes and process instances is automatically provided [2].

If process event logs of suitable quality are available, especially *conformance checking* [3] is perceived as a great instrument to monitor manufacturing processes during runtime [19].

On top of integration and data contextualization, process automation in manufacturing also offers several opportunities with respect to considering data sources in addition to the process event log data that can be analyzed in different phases of the process life cycle A first example for such additional data is time series data as emitted by machines and sensors, e.g., temperature [5]. Process mining has been augmented with dynamic time warping on sensor data for predicting and explaining concept drifts, i.e., upcoming process evolution due to, for example, chips on the parts causing decreasing quality [20]. Another example for additional data relevant to manufacturing are engineering drawings and standards such as ISO norms. Engineering drawings contain the essential information for setting up the manufacturing process and the subsequent quality control, i.e., the dimensions of the produced parts and tolerances, together with links to the underlying standards [15]. DigiEDraw [15], for example, provides

[5] `https://www.celonis.com/solutions/systems/sap/`

conceptual and tool support to automatically extract this information from the drawings such that they can be included in the process models, but also in process analysis. Approaches such as [22] provide NLP-based concepts and tools to check the *compliance* of (manufacturing) processes with regulatory documents.

5 Discussion and Outlook

We refer back to the questions set out in the introduction: 1) How to automate manufacturing processes? It depends on the starting point (legacy vs. greenfield, and in between) and raises many (technical) challenges, e.g., how to connect machines to the process. 2) What are the specifics with respect to the involvements of humans? Humans are always involved, either active or passive. If active, the involvement ranges from working on tasks (interface: worklist), over being supported (interface: UI), to interactively working on and designing the process (interface: loading station). As a lesson learned, physical devices can serve as interfaces between process and human, as well. 3) How do the automation strategies impact process mining options and vice versa? Process mining quality heavily depends on data collection and quality which an be provided by process automation. Process mining can go new ways by integration of process event logs with additional data such as time series. These findings for manufacturing are likely to be relevant for other domains with similar requirements such as health care or logistics, as well.

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