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Efficient data acquisition for traceability and analytics

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Abstract

Implementing processes for traceability is required in various industries to assure product quality during manufacturing, provide evidence on required processing conditions or facilitate product recalls. Commonly, radio-frequency identification (RFID) or code recognition techniques (e.g. Data Matrix) are applied to track the flow of workpieces through a manufacturing system and link processing data accordingly. Although the analysis of tracking data is well-examined, we still see a gap in the research on the trade-off between data acquisition, data analytics and data quality. Here, we present a framework to increase the value of existing data by enabling data analytics while addressing common pitfalls and reducing the costs of data management.

Keywords: Identification; Knowledge management; Manufacturing system; Process control; Quality assurance; Sustainable development; Decision making; Complexity; Analysis; Design

1. Introduction

With the increasing integration of digital technologies in the manufacturing industry, it is necessary for companies to not only have means for data acquisition and analytics implemented but also to keep accompanying processes simple and efficient. Here, we focus on the collection and usage of traceability data. The implementation of processes and software to support the traceability of workpieces is required in various industries in order to assure product quality during manufacturing, provide evidence on required processing conditions or facilitate possible product recalls.

Furthermore, the analysis of traceability data can support performance evaluation of manufacturing systems and facilitate model building for material flow simulation [1]. Although the analysis of traceability data can support continuous improvement of manufacturing systems, often the cost of collecting data and maintenance of high data quality over time is not considered. However, continuous improvement processes are crucial for increasing the efficiency of manufacturing systems. Given the significance of sustainability (c.f. [2, 3, 4]), these processes may address economic, environmental and social challenges.

Accordingly, we provide a framework to support the tracking of workpieces throughout the production line while avoiding common issues of data quality and enabling insightful data analytics. We structured our contribution as follows. After the introduction, related work is discussed before extensively motivating our framework. Subsequently, the methodology is introduced and eventually a conclusion is drawn.

2. Related work

As far as manufacturing data is considered, general methodologies may be applied to address challenges of data management [5, 6]. Especially, the concept of data value chains (c.f. [7]) and their stages of data generation, data acquisition, data curation, data preprocessing, data analysis and data exploitation are discussed [7].

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Data acquisition can be classified as manual, semi-automatic and automatic based on the implemented degree of automation [8].

Frequently, the term data analytics is used to describe an interdisciplinary approach and its implementation for retrieving knowledge to solve complex challenges [9]. Generally, data analytics can be categorized into business intelligence and advanced analytics [9]. The former category includes descriptive and diagnostic analytics, while the latter category comprises predictive and prescriptive analytics [9]. In this context, various techniques are described, such as data mining [10], process mining [11], visual analytics [12] and knowledge extraction [13].

As far as traceability is considered, numerous approaches to data analytics along with their underlying data schemes have been published [1, 14, 15, 16, 17, 18, 19, 20, 21, 22, 23, 24, 25]. However, best practices of data acquisition and the issues of data quality are rarely considered. Though, the quality of gained insights through data analytics may depend significantly on the quality of the analyzed data. In fact, data quality does have manifold facets [26]. Here, this gap should be narrowed as we discuss a framework for the efficient acquisition of tracking data while focusing on data management and keeping the potential of data analytics in mind.

3. Motivation

Traceability is often a legal requirement and involves the tracking and tracing of workpieces. Tracking "describes the identification, acquisition, and storage of upstream information" [27] for any given workpiece. In contrast, tracing enables "the extraction of this saved information downstream its life cycle of a workpiece at a later stage in the value chain" [27]. Often, the traceability data is complemented with quality monitoring data. Here, we mostly focus on tracking information.

Commonly, radio-frequency identification (RFID) is applied in order to track the timed flow of RFID-tagged workpieces through a manufacturing system. Typically, a gate-based or waypoint-discrete approach is considered for data acquisition, i.e. data is gathered when entering or exiting a certain zone, station or any waypoint. Alternatively, a time-discrete approach of tracking can be considered where localization systems cyclically capture the time and the location of a workpiece within a factory.

Additionally, process quality data can be collected when starting or completing a processing cycle at a certain station [28] (e.g. drilling, machining). The gathered data may then be stored on the RFID tag itself (data on tag) or in a dedicated database along with an identification attribute (e.g. electronic product code) of the related RFID tag (data on network) [29]. Typically, the data-on-network storage regime is preferred as it allows for the analysis of a centralized data set.

Alternatively, text or code recognition (e.g. Data Matrix, Quick-Response (QR) code) may be utilized to identify marked workpieces (e.g. laser engraving, laser tempering, dot peen marking), while feature recognition (e.g. shape, dimension, weight) can be used to identify unmarked workpieces.

Typically, the scope of tracking is determined by single workpieces or batches of workpieces that are tracked either directly or indirectly. In case of direct tracking, identifying tags or features are bound to single workpieces. In contrast, with indirect tracking various means of workpiece transportation (e.g. workpiece fixtures, containers) are identified and, thus, information related to the contained workpieces can be persisted.

However, processes for the acquisition of tracking data may be physically constrained by the manufacturing environment, e.g. dimension, shape, material of workpieces or fixtures as well as environment-induced potential of interferences within certain frequency bands. Therefore, certain manufacturing sites may require a combination of various technologies, techniques and scopes of traceability paired with methodologies for data integration.

Additionally, the specifics of identification technologies could affect data quality. For example, an impeded line of sight (e.g. dirt, obstacles) or interference can cause missing data. Furthermore, accidental bulk scanning of RFID tags without adequate signal post-processing may lead to redundant data.

Somewhat independent of the implemented technologies for workpiece identification, organizational challenges can cause additional issues of data quality. Therefore, human error should be expected when implementing or performing [8] data acquisition processes. Additional challenges may arise from continuous improvement processes and changing requirements resulting in product alterations, manufacturing systems and logistics, i.e. issues of flexibility, modularity and scalability should be considered.

The potential of data analytics and the ability to generate valuable insights should be considered as well. In fact, the analysis of tracking data can reveal valuable knowledge about operation times [22, 24], idle times [23] as well as lead times [18] and even more properties [1].

The presented aspects, to some degree, not only illustrate the complexity, costs and expenditure of time but also potential benefits related to the implementation of tracking data acquisition processes. Therefore, we provide a framework and share best practices for the acquisition and management of traceability data to overcome certain organizational challenges.

For reasons of simplicity and somewhat independent of the various implementation technologies, we solely focus on the direct, waypoint-discrete tracking of single workpieces along with data-on-network storage. However, our research may be transferred to scenarios of indirect tracking accordingly.

4. Methodology

In the following, we present our methodology for data acquisition and discuss inherent issues of data quality. Therefore, we start by describing the considered use case from the automotive industry. Subsequently, the procedure for data acquisition as well as the underlying data scheme are outlined and techniques for ensuring data integrity are proposed.

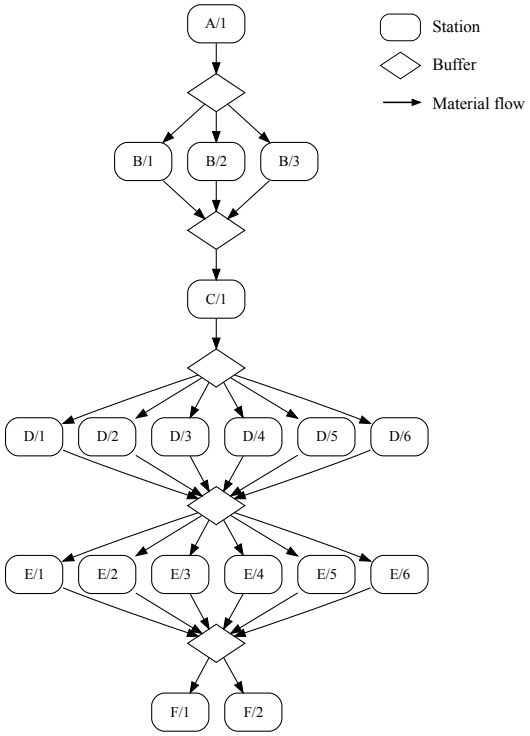

Fig. 1. Overview of a high-volume production line at an automotive company

4.1. Use case

We base our discussion on the acquisition of traceability data on a high-volume production line of an automotive company (Fig. 1). There, any raw part is incrementally refined along a flow shop with multiple groups of stations at a defined takt time. Within a group, every station can execute the same manufacturing operations and, thus, every station is interchangeable with every other station from that group. The material flow between groups is decoupled by means of first-in, first-out buffers (queues). Every workpiece, independent of its type, must be processed at one station from each group in the sequence of the indicated material flow. The automotive company operates many production lines comparable to the one described here. Consequently, the continuous improvement processes of the company may significantly benefit from transferable, scalable and efficient data acquisition techniques.

4.2. Data acquisition

In consideration of the previously introduced use case, we suggest the acquisition of tracking data on completion of a processing cycle for each station as depicted in Fig. 2. In doing so, a waypoint-discrete data acquisition scheme is implemented. We prefer a waypoint-discrete tracking regime over a time-discrete tracking regime, as in many cases existing data acquisition processes are designed with respect to station-oriented process control and quality assurance. Consequently, most companies inherently follow a waypoint-discrete scheme to data acquisition, which can be adapted to support workpiece identification and tracking. Additionally, time-discrete data is often algorithmically processed to find a waypoint-discrete approximation [23, 30].

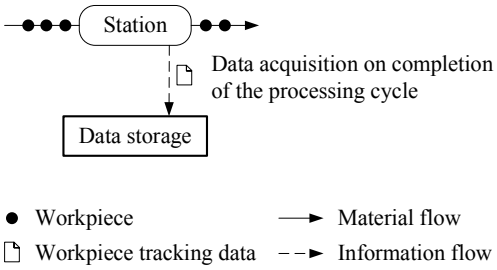

Fig. 2. Data acquisition based on [1]

Frequently, it is mandatory to acquire data at the completion of a processing cycle, since process monitoring data (e.g. pressure or temperature measurements) may only be fully available at that point of time. In contrast, we do not necessarily have to acquire data at the start of a processing cycle. This is due to the fact that cycle times and virtual start of a processing cycle can be retrieved implicitly from data solely collected at the completion of a processing cycle [1]. We also argue that it is not necessary to collect data dedicated to buffers, as buffer capacity and load may be implicitly determined from data solely collected at the completion of a processing cycle, too [1]. The guaranteed accuracy of the implicitly retrieved properties should be sufficient in many cases. However, the achievable accuracy may be discussed under some circumstances [1].

The discussed procedure is generally suitable for automatic and manual data acquisition, although one should take into account human error when manually scanning workpieces. With respect to the introduced use case, a set of workpieces are often processed before any of them is being scanned. Consequently, acquired data may not adequately represent the sequential execution of manufacturing tasks and it may be hard to determine an adequate approximation of the processing cycle time (c.f. [1]).

4.3. Data scheme

The tracking data set may be formalized as a series of events with various attributes (1). The definition can be understood as a *workpiece* of some *type* being fully processed at a certain *station* and *time* (Table 1). We discuss each attribute and common issues of data management and quality individually in the following.

$$Event := \{\, Workpiece, Type, Station, Time \,\} \tag{1}$$

4.3.1. Workpiece

The workpiece is represented by a coherent (alpha-numeric) identification code. In many cases, RFID tags already come with a globally unique electronic product code that can be scanned. So, the reuse of this code may be suitable. However,

Table 1. Exemplary entries of acquired tracking data

Workpiece	Type	Station	Time
B023D	F4	C/1	2021-01-07 08:04:08
F4683	F4	F/1	2021-01-07 08:04:19
E49F2	F4	A/1	2021-01-07 08:04:26
123C0	B2	A/1	2021-01-07 08:04:27
70A14	F4	C/1	2021-01-07 08:04:38

as RFID tag initialization is outsourced, certain informational and procedural dependencies on the supplier of the RFID tags are created. This method may preferably be used when RFID is the only identification technology utilized, as the code would need to be replicated for the various implemented identification technologies in an additional work effort most likely even beforehand of any processing. However, using RFID only, while achieving neglectable benefits in many cases, may cause an unnecessary restriction and, thus, affect flexibility of the data acquisition system as well as manufacturing system. Alternatively, a data acquisition system for the storage of traceability data can generate a company-wide unique identification code for workpieces that can be stored on any writable RFID tag or encoded as a Data Matrix or QR code accordingly.

Frequently, buying businesses request a certain scheme of product identification based on their individual logistic and assembly processes. Derived requirements for workpiece identification may concern not only the utilized identification and marking technologies but also the encoding of data attributes. These specifications often vary across multiple buying companies. Additionally, it effectively is impossible to foresee changes in future buyer-specific requirements. We therefore argue against the integration of these buyer-specific requirements into a company's workpiece identification scheme. Instead, we propose a two-code strategy, where a primary code enables the company's internal workpiece identification and an optional secondary code may fulfill the buyer-specific product identification requirements. The workpiece may be distinctively marked with the secondary code at the final stage of production in order to avoid an organizational conflict with the primary code.

Consecutive numbering of workpieces according to their first arrival at the production line is beneficial for data visualization and analytics (Fig. 3). In doing so, the dispatching of workpieces, the output of various groups as well as any alteration in the chain workpieces caused by manufacturing disturbances is inherently apparent. Please note that we can derive a consecutive numbering of workpieces if not already existent. Therefore, we first need to determine the starting point of the production line, e.g. the first station in flow, and then filter the series of events (c.f. Eq. 1) to match the specified stations and sort them based on the time of their process completion. When iterating over the remaining and sorted series of events, we can map the initial workpiece identifier (without consecutive numbering) to a new incrementally increased sequential workpiece identifier (achieving consecutive numbering). When applying post-processing for the generation of sequential workpiece identifiers, new identifiers may be generated according to

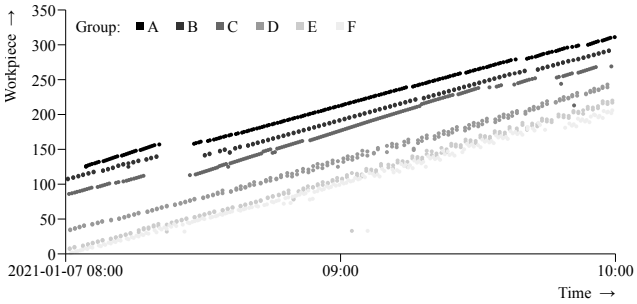

Fig. 3. Tracking of workpieces with consecutive numbering across various groups within a manufacturing system

one's liking considering different scopes determined by the respective time frame or production line and segment. In doing so, human comprehension may be facilitated when applying multi scope visual analytics.

4.3.2. Type

Considering the type of workpieces in tracking data allows for type-specific data analytics, e.g. the identification of scheduling strategies. We recommend using an already existing type identification attribute based on existing engineering documentation and data management.

4.3.3. Station

We recommend a commonly-practiced hierarchical naming scheme according to the doublet pattern *group/station*, where a certain *station* is related to a certain *group* according to the similar manufacturing tasks in the direction of material flow. Here, for reasons of simplicity, we propose the doublet pattern *group/station* as in *B/1* where the group is determined alphabetically according to sequence of manufacturing operations within the material flow while the station is identified numerically within that particular group. However, the pattern may be extended hierarchically to account for various production lines and different manufacturing sites to *site/line/group/station* according to the anticipated scope and level of detail.

Please note, it may be beneficial to apply a naming scheme that allows for extending the manufacturing line with additional sites, lines, groups and stations while optionally maintaining implicit ordering, e.g. according to material flow or position.

4.3.4. Time

We suggest representing date and time according to ISO 8601 [31], where the lexicographical order can be used for chronological sorting. In most cases, the consideration of time with second precision should be sufficient for use cases in manufacturing.

When working with date and time, various time zones and occasional switching between standard time and daylight-saving time should be considered with respect to the location of any considered manufacturing site and the possibility of global remote data access. We therefore suggest the acquisition of tracking data according to coordinated universal time (UTC) and adjusting the presentation of data and analytical findings

for the contextually determined time zone on demand. Thus, time data management with respect to the acquisition of tracking data is streamlined while providing a context-aware user experience when presenting data and analytical findings.

Additionally, (redundant) time synchronization services may be utilized to occasionally adjust for timing drift of data acquisition hardware and storage services. We would like to point out the disadvantage of manual scanning, as the timing of scanning workpieces and data acquisition may not adequately represent the planned modus operandi of manufacturing. Additionally, data may be acquired redundantly or not at all. However, this disadvantage may be neglectable if adequately taken into consideration when interpreting data and analytical findings. Still, we recommend the implementation of some sort of automatic data acquisition system for each station.

4.4. Data integrity

Given the introduced data specification, we briefly describe some approaches for ensuring data integrity. As mentioned before, we suggest naming of groups in an alphabetical order according to their sequence within the material flow of a production line. In fact, the tracking data events for every workpiece sorted chronologically should reproduce the sequence of groups within the material flow. We can leverage these independent prerequisites to compare both and point out discrepancies if existent.

We also can check for redundant entries in terms of the acquired data indicating one workpiece passing one group within the production line at least twice. However, redundant data may be plausible when rework of workpieces within a group is supported. Every check may be run cyclically and automatically to allow for early detection of data quality issues and their correction as well as the improvement of the causing data acquisition processes.

5. Conclusion

We describe a framework for the efficient acquisition of tracking data while keeping the possibilities of data analytics in mind. The framework somewhat follows the paradigm of efficiently creating more value from less data. Therefore, the complexity implied by the acquisition of tracking data serves as the motivation of our framework. The methodological elaboration is supported by an industrial use case from the automotive industry. Subsequently, based on a waypoint-discrete scheme for the acquisition of tracking data at the completion of a station's processing cycle, we discuss the data scheme and its attributes while data quality and opportunities of data analytics are considered.

The framework facilitates data analytics and allows for implicitly retrieving some approximation of properties of a manufacturing system, i.e. the explicit acquisition of these properties is not necessary. Additionally, best practices are introduced, e.g. supporting visual analytics or the handling of various time zones in globalized manufacturing scenarios or remote data access. Future work should more deeply examine the opportunities of data analytics for retrieving implicit knowledge (c.f. [1]), automatic simulation model generation (c.f. [32]), streamlining data acquisition and managing data quality. Findings may then be transferred to different areas such as status message management (c.f. [33]), energy management (c.f. [34]) or even the design of product-service systems (c.f. [35]).

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