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Retrieving properties of manufacturing systems from traceability data for performance evaluation and material flow simulation

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Abstract

The operation of manufacturing systems is increasingly accompanied by data-driven continuous improvement processes and product traceability is required. Commonly, radio-frequency identification (RFID) technology is applied to track the flow of a uniquely-identifiable workpiece along various stations or waypoints within a factory. Based on an automotive use case, this paper describes how to analyze the resulting traceability data in order to identify several properties of a manufacturing system. The acquired knowledge can support performance evaluation and facilitate model building for material flow simulation as a foundation for digital twins and cyber-physical production systems.

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1. Introduction

Effective data management strongly affects the commercial success of manufacturing companies [1]. The aggregation and filtering of alarm data can support the handling of machine failures [2]. Decision-making in manufacturing planning, control and operation can be supported by the visualization of data, energy consumption modeling (c.f. [3]) or the simulation of various operational strategies [4]. Additionally, data analytics and machine learning can be utilized to achieve improvements in manufacturing beyond human capabilities [5].

Following market demand or legal obligation, companies often have to implement data acquisition processes to assure product traceability [6]. This paper describes a validated approach to generate additional value from existing traceability data. Various properties of a manufacturing system can be retrieved using the developed methodology for data acquisition and analysis. For this purpose, a visual framework is introduced in order to increase manufacturing transparency and support continu-

ous improvement processes, while simultaneously allowing for human review of the property retrieval process. The acquired knowledge may be used to create a material flow simulation model, thus reducing manual efforts for data collection, analysis and model development, while contributing towards the automatic generation of simulation models (c.f. [7]).

In the following, the state of the art is presented first. Subsequently, based on an overview of the developed methodology, the data acquisition scheme as well as the actual process of data analysis is described. Eventually the findings are discussed and a conclusion is drawn.

2. State of the art

Commonly, traceability data for a single workpiece is acquired using radio-frequency identification (RFID) or optical identification technologies (e.g. Data Matrix), while the applied data acquisition practice allows for waypoint-discrete or time-discrete tracking of workpieces as described in the following.

In case of waypoint-discrete tracking, workpiece-related data is collected on occurrence of a manufacturing event at a certain waypoint, e.g. workpiece arrival at a defined warehouse zone or process completion at a station. The location of a workpiece is then provided by means of the respective waypoint, i.e. station, machine or zone. Frequently, additional information to account for processing quality at a certain station is stored and linked to the respective workpiece or batch of workpieces. Waypoint-discrete tracking data can be analyzed in order to retrieve operation times as well as dispatching rules [8, 9]. Furthermore, it is utilized to address issues of scheduling [10, 11] and manufacturing performance evaluation [12]. Recently, the generation of descriptive models or petri nets for manufacturing systems is addressed by [13–16], thus pointing out a relation to process mining (c.f. [17]).

In case of time-discrete tracking, localization systems capture the location of a workpiece on the shop floor cyclically. That is, a corresponding data entry often contains a unique workpiece identifier, the current point of time as well as the current workpiece location by means of coordinates within a factory. Data analysis can unveil a rough structure of a manufacturing system based on average workpiece movement and idle time [18], i.e. time-discrete tracking data is analyzed to identify certain waypoints. Further examination then allows for lead time determination [19] and, given additional context information, even more properties of manufacturing systems can be obtained [20].

This paper focuses on the discovery of various properties of manufacturing systems from waypoint-discrete tracking data that is collected whenever the processing of a workpiece is completed at a certain station. Additionally, this work provides an adequate visual framework for human comprehension of the information retrieval process and therefore exceeds the presented state of the art.

3. Methodology

In many cases, time-discrete traceability data is geospatially clustered and, in consequence, partially transformed to waypoint-discrete data (e.g. [18, 19]). Therefore, this paper solely focuses on the acquisition and analysis of waypoint-discrete traceability data. The respective methodology is illustrated in Fig. 1, where workpiece-related data is acquired on completion of a station's processing cycle and stored accordingly. The database then can be analyzed in order to gain valuable insights about a manufacturing system. The acquired knowledge may then support manufacturing performance evaluation or model building for material flow simulation as part of a continuous improvement process.

4. Data acquisition

Product tracking data is often heterogeneous due to the manifold data interfaces and naming conventions applied at various companies. Additionally, measurements specific to process, station and utilized sensor may have to be monitored. However,

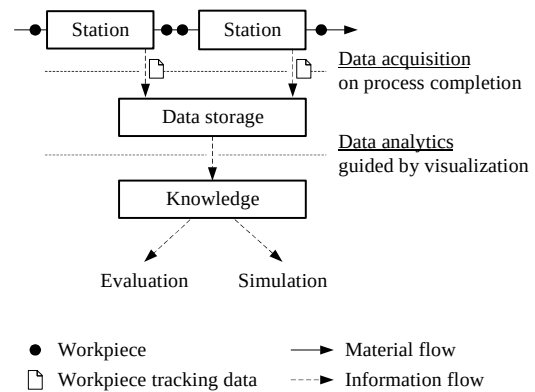


Fig. 1. Methodology for waypoint-discrete data acquisition and analysis to support manufacturing evaluation and simulation.

the presented approach is based on a concise data scheme with values that are most-commonly collected (Eq. 1).

$$Event := \{Workpiece, Station, Time\} \quad (1)$$

The data scheme corresponds to an event of processing completion of a uniquely-identifiable *workpiece* by a specific *station* at a certain point of *time* as illustrated in Table 1, where it already becomes obvious that station *B/3* is able to process at least two workpieces simultaneously.

Table 1. Data example for waypoint-discrete data acquisition based on Eq. 1.

Workpiece	Station	Time
BB90F	B/3	2020-10-08 08:00:07
0184A	B/3	2020-10-08 08:00:07
95A0C	C/1	2020-10-08 08:00:22

Furthermore, each event triplet is subject to the following guidelines.

Workpiece – A workpiece is represented by a unique identifier that can be of alphanumeric format.

Station – A station set consists of one or multiple stations carrying out the same manufacturing task. According to the naming convention used here, a station set is determined by an alphabetic character. Thus, a single station can be identified by its numeric index within a station set (e.g. *B/3*).

Time – The time may be represented according to ISO 8601, while implications of various time zones and the daylight saving time (DST) should be taken into consideration.

5. Data analysis

This section is concerned with the analysis of traceability data provided by the use case of an automotive production line. The use case is briefly described first and followed by a more detailed elaboration on how to retrieve various properties of the production line.

5.1. Use case

The use case is related to a production line of an automotive company. The production line processes any given raw part through different stages of machining, washing and assembly.

The line is structured as a flow shop by means of multiple station sets, where each station within such a set carries out the same manufacturing task. The material flow between station sets is decoupled by means of first-in, first-out buffers. For most workpiece dimensions, their effect on buffering capacities is negligible. Likewise, processing times vary slightly according to the type of workpieces and its associated machining procedures. Occasionally, workpieces are sidetracked for quality assurance of these machining processes. Rework of workpieces is not considered here.

On the first station of the production line, each workpiece is equipped with an RFID-tag to allow for unique identification of each workpiece. The data acquisition practice of the production line is compliant with the previously introduced data scheme. Therefore, traceability data is acquired as soon as processing of a workpiece at a certain station is completed, which allows for waypoint-discrete tracking of workpieces across the various stages of the production line.

The data considered for data analysis was generated by four station sets (A...D) of the described production line within a two-hour time frame. However, the findings described in the following should be applicable to an arbitrary number of stations and larger time frames.

5.2. Structure

The introduced use case data inherits the flow of each workpiece through the production line. Any workpiece flow can be represented by means of a graph, where each station is mapped to a node and the workpiece flow from one station to the succeeding station is indicated as a directed edge. By representing each distinct workpiece flow within one graph, the structure of the production line is gradually unveiled.

The retrieved structure of the previously introduced industrial use case is illustrated in Fig. 2. The visualization was automatically generated using graphviz (c.f. [21, 22]).

In material flow simulation, system boundaries are commonly determined by a workpiece-producing source and a workpiece-consuming drain. The visualization was extended accordingly: The source node and a respective outbound edge were added before each station without any inbound workpiece flow (i.e. A/1). Likewise, a drain node and respective inbound edge were added after any station without any outbound workpiece flow (i.e. D/1...6).

The stations within the graph were topologically sorted according to material flow dependencies and combined into station sets according to the distance of the shortest path to the system source. Additionally, stations within a set were numerically sorted from left to right based on the respective station index (e.g. B/1...3).

In fact, the structure of the examined production line could be completely retrieved. However, it is required that every sta-

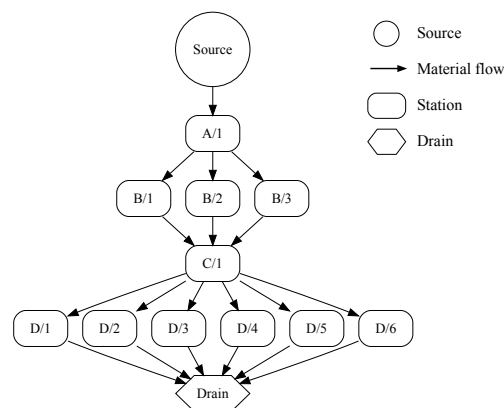


Fig. 2. Automatically generated system topology.

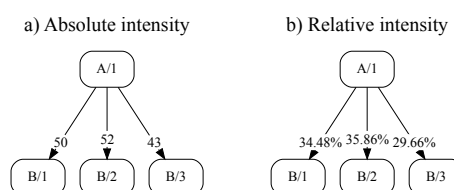


Fig. 3. Extract of the annotated system topology with (a) absolute and (b) relative material flow intensities between station sets A and B.

tion processed at least one workpiece and generated the respective data entry within the examined time frame. If no such data trace is provided, the station cannot be retrieved.

The retrieved structure provides the basis for further annotation of edges and nodes with manufacturing properties, such as material flow intensities, station capacities, processing times, productivity measures and buffering capabilities.

5.3. Intensities

Given the previously generated system structure graph, it is possible to annotate every edge from any station x to any subsequent station y with the total number of workpieces processed at x and y . Hereafter, this number shall be referred to as absolute intensity. Additionally, the relative intensity can be computed for each path between station sets based on the absolute intensities. The computed material flow intensities between A/1 and B/1...3 for the industrial use case, are displayed in Fig. 3.

Please note that incomplete workpiece flows have to be taken into consideration, i.e. workpieces that were processed at station set A but not at station set B and vice versa.

The newly-annotated material flow intensities facilitate the comprehension of work load distribution between various stations. A uniform load distribution is usually desired in manufacturing, as it is in the presented industrial use case. Based on continued monitoring of the situation, suitable measures can be derived and realized in order to improve the manufacturing process. Accordingly, a dispatching strategy can be derived for further refinement of a model for material flow simulation.

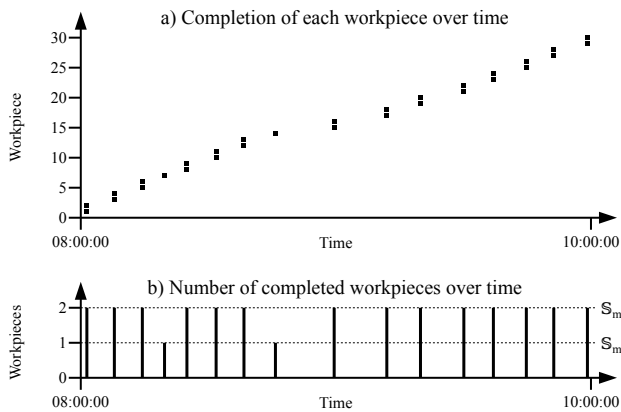


Fig. 4. Estimation of the minimum and maximum capacity (S_{min} , S_{max}) of station D/5 based on (a) workpiece completion and (b) number of concurrently processed workpieces.

5.4. Station capacity

In many cases, stations are able to process multiple workpieces at the same time (e.g. machining centers). It is possible to retrieve the minimum and maximum capacity of a station (S_{min} , S_{max}). For this purpose, the station D/5 of the industrial use case is considered (Fig. 4). By monitoring the completion of workpieces (Fig. 4a) at this station, its capacities (S_{min} , S_{max}) become apparent when simply counting the number of concurrently processed workpieces (Fig. 4b).

Admittedly, the capacities can only be retrieved under the assumption that every possible workpiece station load is realized within the examined time frame and is, thus, inherently represented by the data. As far as the industrial use case is concerned, the minimum and the maximum capacity of each station was identified correctly.

5.5. Processing time

The processing time \mathbb{P} at a station can be retrieved to some degree. To achieve this, the duration between two processing cycles at one station is examined, which may include disturbances, machine setup, loading and unloading. However, there should be at least one occurrence without any of these disturbing influences for a single station and sufficiently large time frame of manufacturing. In contrast, times for station loading and unloading cannot be separated from the processing time, because both are part of the respective manufacturing task. Thus, the minimum time in between two completed processing cycles should roughly correspond to the respective workpiece processing time of a station. The approach is demonstrated in Fig. 5, where the relationship between the completion of workpieces (Fig. 5a) and the duration between several completed processing cycles (Fig. 5b) is drawn in order to retrieve the processing time \mathbb{P} of the station D/5.

For the industrial use case, the obtained processing time for station D/5 is close to the actual processing time. However, a more thorough examination is required to take different times

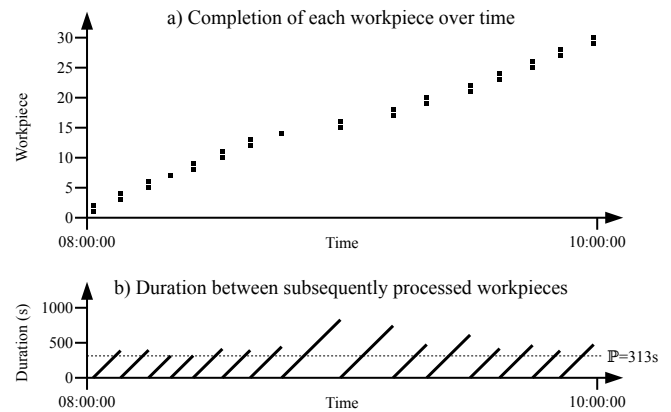


Fig. 5. Estimation of the processing time \mathbb{P} of station D/5 based on (a) workpiece completion and (b) duration between processing cycles.

for processing, loading and unloading of various stations and workpiece types into consideration.

5.6. Productivity

It is possible to approximate a station's productivity. For this purpose, it is assumed that each processing cycle only requires the previously identified processing time \mathbb{P} . The resulting total processing time can be related to the total time frame of examination. Please note that the achieved average station load has to be related to the already determined maximum station capacity S_{max} . The resulting station's productivity can be monitored as part of manufacturing optimization.

However, due to material flow dependencies within a chained production line, the introduced station productivity may account for disturbances occurring at different stations within the system, too. This restriction should be taken into consideration when creating a material flow simulation model.

5.7. Buffering

Based on the retrieved knowledge, the start time of processing at a certain station can be computed by subtracting the previously identified duration of processing \mathbb{P} from the end time of the processing cycle. In order to get an understanding of buffering capabilities between two sequential stations x and y , the workpiece flow can be analyzed.

Given the industrial use case, the workpiece flow between station sets C and D is illustrated (Fig. 6a). The shape created by the displayed flows suggests a first in, first out buffering paradigm. Based on the concurrent number of workpieces in flow (Fig. 6b), the buffering capacity \mathbb{B} is given by the respective possible maximum of workpieces in flow as indicated.

Within the displayed time frame the indicated buffering capacity only circumstantially meets expectations, as several constraints have to be taken into account. (1) A first in, first out buffering strategy is assumed and different buffering strategies are not considered for the time being. (2) Destacking, sidetracking or quality inspection of workpieces may virtually increase the estimated buffering capacity. (3) Commonly, a buffer's ca-

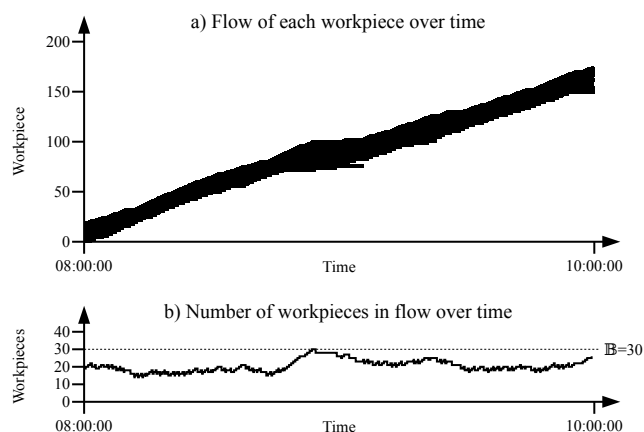


Fig. 6. Estimation of the buffer capacity \mathbb{B} between sequential station sets C and D based on (a) the individual workpiece flow and (b) aggregation of workpieces in flow.

capacity is dependent on the exact dimensions of various workpiece types. (4) It is assumed that at the beginning of the examined time frame, the buffer is empty, which may not be the case at the beginning of the examined time frame of production. (5) The maximum buffer capacity has to be reached at least once within a sufficiently-long time frame of production.

Nevertheless, it can be argued that the provided visualization increases transparency on buffering behavior and, thus, supports manufacturing planning and control.

6. Discussion

This paper proposes an approach for the analysis of traceability data. Thus, existing data acquisition systems as well as methods for maintaining high data quality can be reused for gaining valuable knowledge of a manufacturing system.

However, the application of the methodology is limited by the availability of necessary data, which is generated on completion of workpiece processing at a certain station. Stations without any completed processing task during the examined time frame do not generate any data and, in consequence, cannot be detected. In fact, the deduction of most properties is dependent on a sufficiently large time frame covered by the analyzed data.

Additionally, further restrictions have to be taken into consideration. Especially, processing times or buffering capacities may be dependent on the features of different workpiece types, which has not been taken into consideration so far. Nevertheless, the results from the industrial use case show that a high congruence can be reached, even for complex real-world production systems.

7. Conclusion

This paper describes a methodology for the estimation of various manufacturing properties by analyzing usually required traceability data, hence generating additional value from existing data.

The information retrieval process is accompanied by automatically generated visualizations to facilitate human comprehension as well as continuous improvement of the examined manufacturing system. Furthermore, the automatically estimated properties may be used to build a material flow simulation model.

The methodology was successfully applied to an industrial use case, despite the discussed limitations. Future work could take the implications of various types of workpieces or cyclic material flows into consideration. Further work on automatic model generation for material flow simulation (c.f. [7]) could pave the way for digital twin coupling and cyber-physical production systems (CPPS).

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