Towards a Data-oriented Optimization of Manufacturing Processes

A Real-Time Architecture for the Order Processing as a Basis for Data Analytics Methods

Matthias Blum and Guenther Schuh

Institute of Industrial Management(FIR) at RWTH Aachen University, Campus Boulevard 55, 52074 Aachen, Germany

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Abstract: Real-time data analytics methods are key elements to overcome the currently rigid planning and improve manufacturing processes by analysing historical data, detecting patterns and deriving measures to counteract the issues. The key element to improve, assist and optimize the process flow builds a virtual representation of a product on the shop-floor - called the digital twin or digital shadow. Using the collected data requires a high data quality, therefore measures to verify the correctness of the data are needed. Based on the described issues the paper presents a real-time reference architecture for the order processing. This reference architecture consists of different layers and integrates real-time data from different sources as well as measures to improve the data quality. Based on this reference architecture, deviations between plan data and feedback data can be measured in real-time and countermeasures to reschedule operations can be applied.

1 INTRODUCTION

Dynamic environment conditions, shorter product life cycles and the increasing complexity in the manufacturing environment are just some of the problems companies are facing today. Examples are turbulences in supply chains, shifts in customer demands' or quality problems (ElMaraghy et al. 2012). To counteract these issues, companies need to adapt their processes to these changing conditions (Christopher 2016). Success factors are a high process efficiency and real-time information about processes and objects. Industrie 4.0 is the driving force to secure the competitiveness of high-wage countries such as Germany and to expand their leading position in production technology (Kagermann et al. 2013; Groten et al. 2015). The fourth industrial revolution is mainly driven by the internet of the things and services (Gröger et al. 2016). Industry 4.0 leads to a more resource-efficient and energy-efficient production through the use of intelligent production systems (Monostori 2014; Bauer et al. 2013). Thus, the collection and optimized usage of data within the manufacturing environment is essential to develop intelligent production systems (Gröger et al. 2016; Jeschke et al. 2017). Many example show that the usage of data analytics methods has a high potential to increase the efficiency of value-adding processes (Blue Yonder; IBM; Terradata; Clear Story Data).

The basis for analytics approaches builds a virtual representation of a product on the shop-floor - called the digital twin or digital shadow. The digital twin or digital shadow illustrates the virtual representation of the production through the manufacturing data. Similar to a flight data recorder the relevant data is stored in a time series format (Blum and Schuh 2016). Although, existing IT systems provide feedback data from the shop-floor, they lack a data structure which provides a virtual representation of a product in real-time. Furthermore, the data quality is an important issue that is not addressed in current publications (Abraham et al. 2016). The current state of planning systems can be summarized to:

- insufficient real-time image of the current situation of the production in terms of feedback data
- unstructured data in the variety of IT-systems
- rigid structures and a lack of adaptability of planning systems
- no continuous check of the data and their quality

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- no counter-measures to address the poor data quality

Considering these problems predictions about the future state of the production and reliable statements about the current situation of an order are not possible. In order to overcome the described issue and successfully implement methods of data analytics inside the manufacturing environment this paper presents a reference architecture that overcomes the described issue and provides a virtual representation of a product. Section two addresses basic principles towards a data-oriented optimization of processes. The state of the art regarding real-time reference-architectures is presented in section three and analyzed in section four. Section five introduces the concept for a real-time architecture for the order processing and specifies the different layers. For a prototypical implementation we present and discuss an application scenario in a real production environment. Finally, we discuss und propose further research directions.

2 MOTIVATION

In this paper, the term analytics in association with business intelligence is defined as follows: It is understood as a scientific process of mathematical-logical transformation of data to improve decision making. The maturity level of analytical capabilities can be classified in four stages: descriptive, diagnostic, predictive and prescriptive analytics (Sherman 2015; FAIR ISAAC Cooperation 2013).

To differentiate the four stages, the level of data analysis and human input is analyzed. The descriptive analytics, the first stage, aims at analyzing large amounts of data to get an insight of what happened in the past. It answers the question "What happened?". By analyzing the interactions within the data with the purpose of getting a conclusion of why it happened in the past. Thus, diagnostic analytics answers the question "Why did it happen?". The question "What will happen?" is covered by predictive analytics. Predictive and prescriptive analytics support proactive optimization. Future behavior is predicted by methods of pattern recognition and the use of other statistical methods. The last stage, called prescriptive analytics, answers the question "What should be done?" by using simulation and optimization algorithms to suggest or directly implement a concrete measures. (Stich and Hering 2015).

3 STATE OF THE ART

Although, several publications focus on approaches regarding real-time architectures which assist in planning and controlling the manufacturing process, a scientific investigation of a real-time representation of a product is only performed in very few research activities and not dealt with in detail. Furthermore, measures to improve data quality are not mentioned. In the following chapter these approaches will be outlined.

ZHANG ET AL. 2014 develop a framework for a real-time data acquisition in production and the integration of the internet of manufacturing things (IoMT) into business information systems. The AutoID-system based IoMT provides real-time information and status for a dynamic decision making. Supplied by RFID tags and machine data the sensor network enables real-time tracking of the resources and forms an interface between the production and the superior management information systems. The data structure of the processing layer was developed according to the international standard ISA95 and operates with the B2MML for data exchange. (Zhang et al. 2014)

GUO ET AL. 2015 develop and implement a RFID-based system architecture for the decision-making process in the production monitoring and planning of a decentral manufacturing. It is developed for the application of production planning in the decentral textile industry, which is characterized by highly fluctuating order processes, to generate more transparency about capacities of the locations. It uses RFID-technologies to collect data, which is analyzed and reconditioned in a module for a business wide access. This data is presented in a task-specific way and every incoming order will be assigned by a production model to fabrics and production. (Guo et al. 2015)

LUO ET AL. 2015 develop a real-time capable production planning for a hybrid flow shop using a RFID technology linked production environment. Luo et al. aim at optimizing the production planning considering the current progress of an order. To create a distributed and linked production within the meaning of ubiquitous computing active RFID reader and passive RFID tags are used as parts of smart objects. The shopfloor gateway connects every working cell gateway, which combine and represent all RFID objects, with the equivalent production and it also connects the production with the superior information system. In addition, the shopfloor gateway processes the production data by means of the workflow management module, a MS-UDDI server for data distribution and module for monitoring the working cells. For the schedule of the hybrid flow shop a multiple periodical hierarchical production planning algorithm is used. (Luo et al. 2015)

ZHANG ET AL. 2015 develop a method for controlling a non-clocked material flow based on real-time information. Based on the real-time information from the assembly line, exceptions in order sequence as well as the reaction to failures should be better controllable, since information about disturbances is recorded directly at the place of origin. To collect and distribute real-time information, Zhang et al. desig an RFID-based system to support the flow through the use of recorded data. The recorded data is processed by the developed method in the three service processes, who track and support the workflows on the shop floor. Besides the three service task a second core task handles the data exchange with the upstream and downstream workstations. The information can be used to adjust the order scheduling process based on real-time information. (Zhang et al. 2015)

ZHONG ET AL 2015 design a model for an advanced production planning and control based on RFID technology. In addition to improve production planning and control via a second-level hierarchical approach, the goal is to develop and disseminate guidelines for the implementation and use of a linked production based on a RFID system. Therefore, the production is equipped with smart manufacturing objects and the production planning and control is dimensioned for a multi layered hybrid flow shop. The first level of PPS sets the sequence of orders considering its priorities. The second level determines the production plan, where orders are divided into small tasks and added to a job pool. The RFID network provides real-time data for the planning and the evaluation of the planning and control regarding the usability and benefit. (Zhong et al. 2015)

KASSNER ET AL. 2015 present a platform and reference architecture for the integration and analysis of structured and unstructured data. The presented platform ApPLAUDING consists of three layers to integrate, analyze and present the structured and unstructured data form different sources. To integrate the data, a mechanism similar to the ETL-Process extracts and provides it to the second layer. The second layer is divided into core analytics and value-added analytics. The last one provides fully-fledged analytics. The presentation layer provides a user interface where the analyzed data is presented. (Kassner et al. 2015)

YANG ET AL. 2016 provide an RFID-enabled indoor positioning method for a real-time manufacturing execution system using an extreme learning machine (ELM). For the localization the signal levels of RFID tags are analyzed by an adaptive regression algorithm. The ELM is an algorithm with just one layer of hidden neurons, which is characterized by a high adaptability and ability to generalize. The algorithm for localization is imbedded into a RT-MES layer and transfers position data to superior layers. The ELM needs the data and various activation functions for training and validation. (Yang et al. 2016)

GRÖGER ET AL. 2016 provide with Stuttgart IT Architecture for Manufacturing (SITAM) conceptual IT architecture for a data driven factory. The architecture consists of three layers that process the data of the digital factory and provide it to the user. In the first layer the data will be collected and a flexible integration of heterogeneous IT systems is guaranteed. The second layer of the SITAM analyzes the data and provides it to the third layer, where the data is send to manufacturing-specific mobile apps. Gröger et al. give an overview of possible implementation scenarios and the benefits of the SITAM. (Gröger et al. 2016)

SCHUH AND BLUM design a data structure for the order processing which aims at providing a virtual representation of a product during manufacturing, called the digital twin or digital shadow. This data structure provides a real-time feedback data in a time series format and overcomes the lack of current IT-systems. Therewith, conclusions about past incidents and a real-time status of an order contribute to improve manufacturing processes. (Blum and Schuh 2016).

4 REFERENCE ARCHITECTURE AS A BASIS FOR DATA ANALYTICS

In this paper we present a real-time reference architecture for the order processing as a basis for data analytics. The reference architecture consists of three layers. A data layer, an integration layer and a presentation layer (see Figure 1). Based on the derived requirements for a real-time architecture we will detail the different layers in the section.

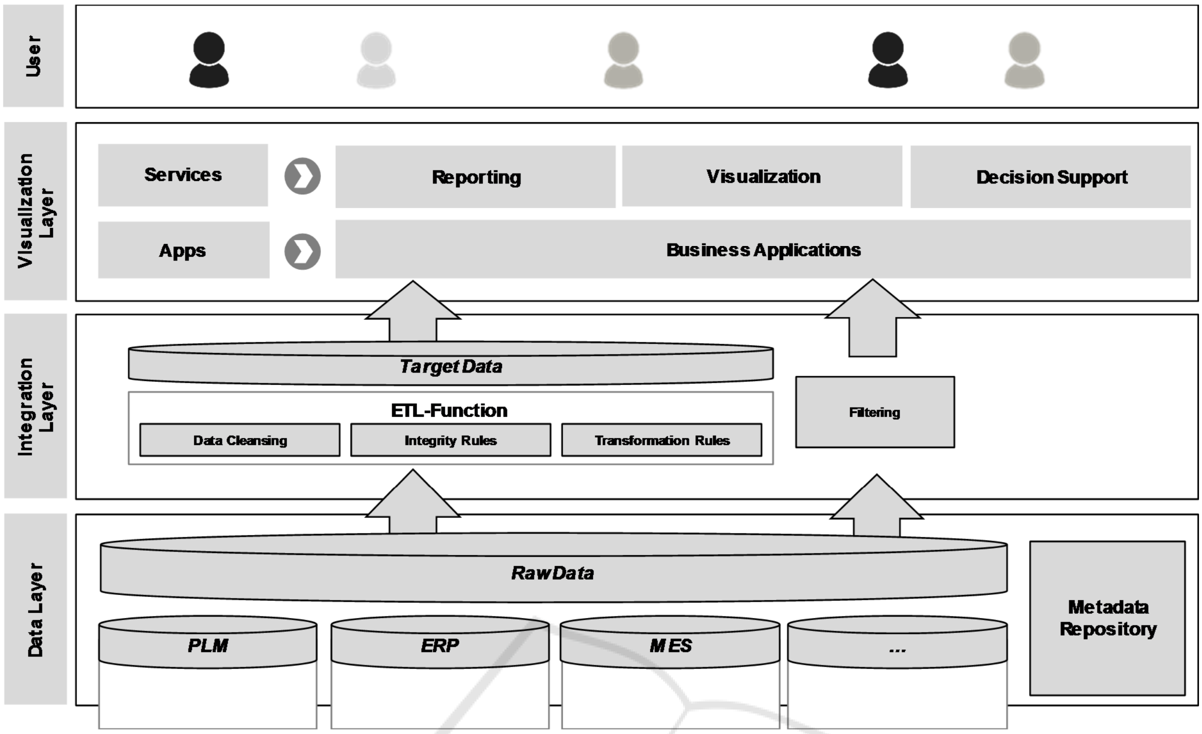


Figure 1: Reference Architecture as a basis for data analytics.

4.1 Data Layer

The data level integrates data from different sources into a database. For a holistic image of a product on the shop floor tangible aspects (e.g. the product, the workstation, etc.) as well as intangible aspects (e.g. process plans, the geolocation, the status, etc.) are required. A detailed description of the data structure can be found in (Blum and Schuh 2016). The identification of the required data can be determined by with regard to the following aspects:

- Relevance of the data to the production control
- Automatic data acquisition based on sensors without manual data input
- Real-time acquisition of the data

The primary application for the developed data structure will be single or small batch production. Thus, a special focus will be on linear and divergent production structures, the use of alternative resources and different operations and a semi-automated production with a high degree of manual process steps. Based on the production structure transport and temporary inventories will be considered. The derived data structure is presented in Figure 2.

To meet the different needs for a real time image of an order in the form of a digital shadow time related data is required to specify the time and date when the data is recorded. Herewith, an entire data record from the release until the completion of an order on the shop-floor is made possible. This concept is comparable to an airplane's flight data recorder where data is collected in a time series format and

Date	Time	Order	Product	Geolocation	Workstation	Process	Status
10.01.2016	10:00:01	4711	A1234546788	90, 40	140	--	waiting
10.01.2016	10:00:02	4711	A1234546788	90, 40	140	--	waiting
10.01.2016	10:00:03	4711	A1234546788	90, 40	140	10	set-up
10.01.2016	10:00:04	4711	A1234546788	90, 40	140	10	set-up
10.01.2016	10:00:04	4711	A1234546788	90, 40	140	10	failure
…	…	…	…	…	…	…	…

Figure 2: Data structure for a real-time image of an order. (Blum and Schuh 2016).

stored. The database keeps time-related features by storing sequences of each value that change with time. In contrast, a relational database usually stores just the most recent value. The time-series format allows to find unique patterns in the data, which are usually related to trends of changes. In the case of an airplane trends related to velocity or oil pressure can be revealed. Transferred to the order processing deviations from the schedule (e.g. geolocation, workstation and set-up time) may occur and can be detected in real-time. Time data represents the leading characteristic of the data structure. Therefore, other items of the data structure must refer to it.

Overall aim of a production system is the manufacturing of the right products in the right way and quantity, in the correct quality to a specified date and acceptable costs (Westkämper and Decker 2006). With the use of operational resources, a transformation process of raw materials or semi-finished products into finished parts or products takes place (Westkämper and Decker 2006). Initial object of each product is an order from a customer. In a manufacturing environment, we assume there exist different orders and products which belong to these orders, thus each order is a unique identification number assigned. Furthermore, order data incorporates different product identification numbers to determine between different products of an order.

Based on the integration of new sensor technologies (e.g. real-time location system (RTLS) and radio frequency identification (RFID)) a live tracking of an order is possible. RTLS tags are applied to the product or the container and transmit the geolocation. Tracking the geolocation is necessary in order to ensure the routing of the order between two points. This enables to determine the current location of the order. Featured by the use of sensor technologies and a real-time routing, the status of an order between different steps in the working plan can be obtained.

A production process consists of different process steps which are needed to produce a product. Items are tracked in relation to the working plan, e.g., the workstation and the process. These processes can be distinguished according to NYHUIS A. WIENDAHL into the following process steps:

- laytime before and after processing,
- transport time
- set-up time and
- processing time.

Furthermore, the resources on which the operations are performed need to be specified. VDI-Norm 2815 specifies the different resources in a manufacturing environment. These include machines as well as means of transport (VDI 2815).

Based on the current process step carried out the status can be derived and logged. The attributes are defined by the different timestamps in the database. To calculate time related data (e.g. absolute production time, set-up time, transition time) the status is needed. With these information conclusions about the current state of an order as well as ex post analysis are conducted. Based on the data record orders with the same production processes can be compared and reasons for deviations can be revealed. This enables the user to determine on which workstations operations have been performed to complete the order as well as the current operation status.

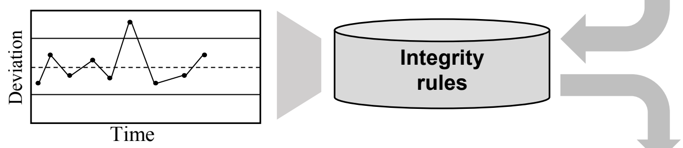
4.2 Integration Layer

The integration layer includes functionalities for securing the data quality. From a product point of view, quality is defined as the processing of a set of characteristics (9000:2015, 2015-11-00). In statistical process control quality has a long history where it is used to ensure product conformity as well as for the optimization of processes. When it comes to data, quality is more difficult to define. Compared to products, data do not have physical properties which allow to assess the quality. According to Wang and Strong the dimensions of data quality can be differentiated in four dimensions and 15 characteristics. For the derived data structure only characteristics are considered which contribute to an improvement of the identified influencing factors and can be measured quantitatively. Therefore, only characteristics like completeness and accuracy are considered in detail. Deviations are defined as the difference between an acquired parameter and its true value. For the derived data structure deviations can occur due to signal losses of the sensors or magnetic interferences. The data is extracted from the different sources using ETL-functions from the integration layer. The ETL-process consists of three different steps. Extraction includes extraction of the data out of the core system and external sources. The transformation step applies a set of rules to clean and transform the data. The last step, loading, ensures that the data is loaded to a target database.

Within Figure 3 the feedback data of a product in a time series format is shown. Although, data was recorded for the date, time, order, product and status without any errors or wrong data, the geolocation contains wrong and missing data. As already explained, these wrong or missing data can occur due

Raw Data

Date	Time	Order	Product	Geolocation	Workstation	Process	Status
10.01.2016	10:00:01	4711	A1234546788	90, 40	--	--	waiting
10.01.2016	10:00:02	4711	A1234546788	**50, 30**	--	--	waiting
10.01.2016	10:00:03	4711	A1234546788	90, 40	--	--	waiting
10.01.2016	10:00:04	4711	A1234546788	**NULL**	--	--	waiting
10.01.2016	10:00:05	4711	A1234546788	90, 40	--	--	waiting
…	…	…	…	…	…	…	…



Target Data

Date	Time	Order	Product	Geolocation	Workstation	Process	Status
10.01.2016	10:00:01	4711	A1234546788	90, 40	--	--	waiting
10.01.2016	10:00:02	4711	A1234546788	90, 40	--	--	waiting
10.01.2016	10:00:03	4711	A1234546788	90, 40	--	--	waiting
10.01.2016	10:00:04	4711	A1234546788	90, 40	--	--	waiting
10.01.2016	10:00:05	4711	A1234546788	90, 40	--	--	waiting
…	…	…	…	…	…	…	…

Figure 3: Changing the data by the application of integrity rules.

to magnetic interferences or signal losses. To detect wrong or missing data and to be able to improve data quality a set of rules is applied to the data structure. These rules are known as integrity rules. For example, a given value is only allowed in a specified range or must contain defined symbols. In the following, we explain how integrity rules are applied to the derived data structure (see Figure 3).

Missing data can be restored by the application of mathematical models. In the area of statistics imputation processes can substitute missing data by estimating the missing values based on other available data in the data structure. Based on hot deck imputation, each of the time stamps is examined and the most similar value is substituted for the missing data value. In the example above, the timestamps before and after the missing data remain at the same values. Based on the most similar timestamps, hot deck imputation can be used to substitute the missing data. In the case of varying geolocation values, mathematical models can be used to estimate and substitute missing values (e.g. linear and non-linear models).

The identification of wrong data inside the data structure takes place by the application of integrity rules. For that, the following rules can be applied. To detect wrong values inside the Geolocation data sets the Pythagorean theorem is used. The Pythagorean theorem is suitable for the distance computation in the two-dimensional space. In this case the theorem is used to calculate the deviation l of Geolocations between two time steps (1).

$$l = \sqrt{(x_i - x_{i-1})^2 + (y_i - y_{i-1})^2} \tag{1}$$

For the example shown in Figure 3, the deviation between the first and second time step is to 41.23 units. If the deviation between two time steps exceeds a predefined range, e.g. more than 10 units, integrity checks will mark the data as wrong. The predefined value could be defined by the distance a production object could be transported by a pallet transporter or automated guided vehicle.

In the data structure, the error may occur that a value of the Geolocation with a deviation occurs between two equal values. This can result in a deviation of status, process or machine.

To check for wrong data in the process order, a state transition model could be used. This model describes the states (e.g. process steps) and the actions that lead to state changes. With such a model a production process order could be described. The integration rules can use the state transitions model to check the process step sequence and, if necessary, enter the correct process step.

After checking the data for incorrect and missing values, the data are cleansed and transformed in the corrected target data. There are various methods to clean up the data. To replace missing or wrong Geolocation data of a moving production object the method of linear interpolation could be used. The hot deck imputation can be used to replace missing or wrong data in other columns of the data structure. The hot deck imputation uses data values of the actual data set to fill the or correct the wrong data. If there is no data for an imputation or a linear interpolation cannot be applied the data record of this time step must be deleted.

4.3 Visualization Layer

In order to make proper decisions, users are usually required to scan and integrate various data sets. Since users mostly act as final decision makers, the complexity of the displayed information can have a substantial impact on the decision quality. To support the user in the decision process, a visualization layer is implemented in the reference model to reduce the complexity of the compared data. The dashboard visualizes the data and especially deviations between the real-time feedback data and the plan data found in the underlying layer of the model. In addition, the dashboard notifies the user about deviations of the order processes on the shop floor. This notifications and visualizations are combined with the upper and lower limits of the allowed deviations.

Furthermore, the visualization layer's dashboard represents both an aggregated view that summarizes all orders, as well as each order and its deviations.

5 APPLICATION

A prototypical implementation based on the derived reference model and data structure to a demonstration factory is ongoing. The Demonstrationsfabrik Aachen (DFA) within in the Campus Cluster Smart Logistic will provide an excellent environment to validate the results of the research in real production area of 1600 square metres. In the DFA an electric go-kart is built. During the production, data is generated and then compared with the plan data to observes changes in the order process. Based on the real time data of an order, deviations in the processing can be uncovered in the moment when the location or the process step differ from the planned ones. Therefore, feedback and plan data are compared with maximum and minimum limit.

6 CONCLUSION AND FURTHER RESEARCH

In this research paper a real-time reference architecture for the order processing as a basis for data analytics is developed which aims at providing a design aid towards a data oriented optimization of manufacturing processes. After introducing the preconditions of the model the structural framework of a reference architecture for the order processing was derived. The reference architecture consists of different layers: a data layer, an integration layer and a virtualization layer. The data layer provides a real-time image in the form of a virtual representation of a product, called the digital twin or digital shadow. Therefore, different data sources (e.g., order, geolocation and status) have to be integrated to derive a holistic image of the order processing. In order to determine the quality of the data, relevant dimensions of data quality for the data structure are derived and integrity rules are formulated. By doing this, wrong and missing data can be identified and data can be restored. The virtualization layer provides the user with the relevant information. Therewith, users can assess the current status of a product in real-time or derive counter measures if deviations between planned and feedback data occur. For enabling the implementation of the model, practical implications have been carried out. The reference architecture builds a framework towards a data-oriented optimization and a basis for the use of data analytics methods. Therewith, conclusions about past incidents and a real-time status of an order contribute to improve manufacturing processes. Further research is needed to substantiate the presented solution principles. Directions of further work include the use of redundant information provided by sensors, the handling of the geolocation and the transfer of the solution principles to other domains (e.g. supply chain and service).

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