A reference architecture based on Edge and Cloud Computing for Smart Manufacturing

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Abstract—**The paper examines the development of production systems from automated to data analysis-supported process control. In current concepts, process optimization is carried out by data analysis with the help of a decision support system after the production process. Prescriptive automation envisages controlling the process before and autonomously on the basis of a prescriptive analytics model. The development of an IT architecture is identified as an essential part of the overall concept. On the basis of expert interviews and current literature reviews, the question is answered, which requirements an IT architecture for prescriptive automation has to fulfill. These requirements are opposed to solution components with the goal of a modular architectural concept. On basis of the requirements and therefore needed solution components, a reference architecture is identified on the assumption of the data processing resources. The main processing components of this architecture are a combination of edge and cloud computing.**

Keywords—edge computing; cloud computing; framework; industry 4.0; smart manufacturing; internet of things; data analytics; prescriptive analytics; prescriptive automation

I. INTRODUCTION

Currently, the control of production facilities follows a fixed logic, whereby dependencies and correlations are considered on a mostly outdated data basis [1]. Digitalization opens up new possibilities to improve decision making with up-to-date and comprehensive data. Presently, existing research in the field of production control with the help of prescriptive analytics mainly deals with general requirements and challenges for individual aspects (e.g. data processing) or individual technologies (e.g. cloud computing). In addition, the extraction of process data for data analysis is often considered, but the analysis and optimization takes place after the production process in form of a decision support system. However, this supporting system still requires a human decision maker and a manual executer [2]. In order to eliminate this deficit, two requirements must be implemented:

1. **Control prognosis model:** An autonomous and proactive control of the production process is necessary to adapt and optimize the process parameters with the help of prescriptive analytics, a so called prescriptive automation. Therefore, it is important to know what happens, what will happen and how to react proactively and autonomously without the human decision maker by the control prognosis model [2].
2. **Model recalculation:** Production conditions usually change over time and require an independent adaptation of the operative control prognosis model. For this purpose, new information has to be gathered continuously of completed process executions and the control prognosis model has to be newly trained and updated.

To enable those two requirements, it is necessary to develop an integrated framework for the acquisition, processing and provision of information for machines and objects. However, enabling the targeted use of large amounts of data (big data) for operational decision-making processes create far-reaching demands on the IT architecture. The main processing components of the architecture are a combination of edge and cloud computing. Since the authors already summarized related work, regarding smart manufacturing with prescriptive analytics, this paper won't expand on the details [2].

From this point forward, the paper is structured as follows: Section II provides an overview of the state of the art. Section III is divided into five categories: control, data acquisition, data processing, connectivity, and data storage. In these five categories, we enumerate the requirements and solution components for the IT architecture. In Section IV, all solution components are summarized and presented in one architecture. Finally, Section V concludes the paper.

II. STATE OF WORK

A. *Machine control in industry 4.0*

Manufacturing has been shaped by three industrial revolutions in the last decades. Currently the production environment is facing a further change, known as the fourth industrial revolution. The objective is to enable all elements of a production facility and supply chain to form a cyber-physical system by merging physical resources with computers and networks [3, 4]. In this way, information processes are further linked in order to make production systems more intelligent and autonomous using learning systems. The aim is to design machines and production systems in such a way that they independently adapt their procedures to different situations effectively [3].

B. *Smart Manufacturing*

Smart manufacturing is a concept for industry 4.0-based control that aims to advance machine control and use data analysis to improve process performance. For this purpose, advanced sensor, control, modeling and platform technologies can optimize production processes [5, 6]. There is a literature

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consensus that production systems which implement smart manufacturing and which are interconnected are more efficient, productive and intelligent than their unconnected equivalents [6, 7]. As a result, the industrial internet of things (IIoT) and distributed computing are pioneers of smart manufacturing [8-10]. As part of smart manufacturing, smart control enables intelligent control of production facilities by real-time interaction. Once a control execution model has been determined, control and optimization methods based on data analysis can be applied [8].

C. *Industrial Internet of Things*

The IIoT, also known as 'industrial internet', is characterized by the integration and cooperation of machines, analytics and people. The aim is to further link the information processes such that objects communicate together beyond their physical boundaries and data is collected that previously could not be captured [11,12]. In the production context, for example, machines, robots, transport systems, workpieces and programmable logic controllers (PLC) communicate with each other and achieve a higher degree of integration. The enormous amount of data enables comprehensive process transparency. As a result, manufacturing processes are more efficient, costs are reduced and quality is increased by adapting the machine procedures to the respective situation [3, 11, 13].

D. *Distributed Computing*

Automation systems have only limited possibilities to collect, store and analyze a large amount of data in distributed environments in real-time. The use of data analytics requires computing power which can be provided using the concept of distributed computing [14].

1) *Cloud Computing*

Cloud computing is a concept for ubiquitous on-demand network access to a pool of computing resources. These can be deployed quickly with minimal management effort and include computing power, storage, databases, and software [15, 16]. From a security point of view, there are two types, private and public clouds. A public cloud describes the service of a provider that is freely accessible via the internet. In contrast, with an private cloud, companies prefer to operate IT services by themselves [17].

2) *Edge Computing*

The concept of edge computing drives the collection and processing of data further into the immediate vicinity of physical devices in production. Therefore, industrial PCs are implemented in the production environment. This provides advantages in terms of autonomy, as such an edge device can operate independently of a central system and can make local decisions [18-20]. Edge computing also simplifies the communication chain and reduces potential sources of error by connecting physical assets directly and collecting, analyzing and processing data directly. An edge device also enables first order operations, such as filtering and aggregating raw data, and it can significantly reduce the transport of large amounts of raw data to the cloud for further analysis [21].

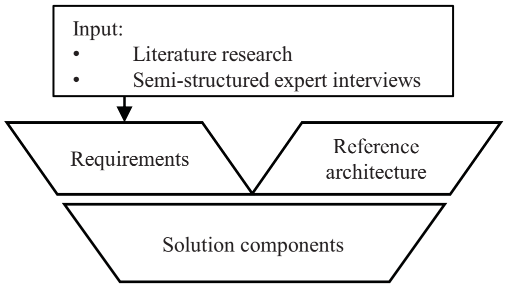

Figure 1. Three steps of specific IT architecture derivation

III. Requirements and Solution Component Analysis

Enabling the targeted use of data for prescriptive automation creates wide-ranging requirements for the IT architecture. The definition of the requirements and solutions for the architecture are described in the following chapters.

A. *Method*

Knowledge of the requirements is the basis for an overall system understanding for a proactive and autonomous control of the production process. Therefore, the objective is a structured collection of requirements, classified according to the main categories relevant for prescriptive automation [2]. In order to collect these, the method is based on the V model, as shown in Fig. 1. The main categories serve as a starting point. From these, more specific requirements are derived regarding an IT architecture for prescriptive automation. In a second step, solution components are compared with the sub-requirements. Finally, these components form together a reference architecture.

The collection and preparation of the requirements was carried out using two complementary procedures: through semi-structured expert interviews as well as through an analysis of the defined requirements and solution components within the scientific contributions from the literature research.

B. *Requirements and Solution Components for Prescriptive Automation*

Based on the semi-structured expert interviews and the literature research the sub-requirements of the main categories control, data acquisition, data processing, connectivity and data storage are listed in detail below. Additionally, the requirements are fulfilled by appropriate solution components detailed in the following chapters. This corresponds to the first two steps of the IT architecture derivation, as shown in Fig. 1.

1) *Control*

Requirements and solution components that are assigned to the control of the production are considered below. The determined data basis is to apply by a suitable application of the control prognosis model for an optimized production control.

Proactive Process Responsiveness

Requirement: Proactive control of processes to react to current states and process deviations must be ensured under real-time requirements.

Solution component: The execution of a control prognosis model makes it possible to respond permanently to changes and optimize production. The control by an edge device, an industrial PC, is recommended. This device has to be located as close as possible to the production process. The spatial proximity and performance of the edge device allows low latency times to be achieved and production facilities to be controlled directly via control outputs.

Control Autonomy

Requirement: The edge device should be able to execute autonomous operations in order to proactively adapt the process to the current execution context without human intervention. Using data analytics and machine learning algorithms, production process relationships are to be determined in order to achieve autonomous process adaptation and product quality assurance in the event of process changes [22].

Solution component: Based on big data, a model is developed and made available in an executable form for operative control on the edge device. This control prognosis model enables a consideration of decision alternatives and a correspondingly optimized decision. A continuous recalculation of the model ensures that a changing context is taken into account without human interaction and is included in the control process [22].

Changeability Control

Requirement: Production conditions usually change over time and require an independent adjustment of the operational control model. This requires the continuous acquisition of new knowledge from the collected data of the completed process executions in order to make these operationally usable. The optimization of the control and thus the self-optimization of the production requires that a change of the control intelligence is cyclically implemented into the control during operation [23, 24].

Automating the integration and delivery processes of the control prognosis model enables fast, reliable and repeatable software deployment. This allows the deployment of the model in the production environment with low risk and low manual effort. The continuous integration/continuous deployment (CI/CD) process provides an approach that reduces the risk of software updates in production through a high level of automation [25].

Control Reliability and Stability

Requirement: Production safety requires the reliability and stability of the control system. The failure of a production plant is only tolerable in rare cases, because failures significantly reduce the overall equipment effectiveness of a plant. However, this can only be achieved through reliable operational control.

Solution component: Based on the resilient software design, two factors are decisive for reliability and stability: mean time to failure (MTTF) and mean time to repair (MTTR). In order to extend the MTTF, three solution modules can be shown: Firstly, the control hardware must be based on industrial hardware with high availability. Secondly, the reliability of the model within the CI/CD process is ensured. Thirdly, the controllers are isolated from each other by virtualization, so that the failure of one control node does not mean a failure of the entire system. MTTR is determined by the maintainability of the control system. Two procedures must be implemented for this purpose: Processes that must be dynamically controlled via operational control must be switched off in the event of a malfunction. On the other hand, less critical processes can be secured by taking over the control from a PLC with a fallback control. This enables a further production operation through a defined static process execution [22].

Independence of Control Hardware

Requirement: Independence and interoperability of the edge device is important for the operational control function. This ensures that the control model is not dependent on special hardware in order to avoid vendor lock-in, i.e. the binding to a hardware system or manufacturer using proprietary technologies [26].

Solution component: Hardware independence makes it possible to guarantee longer availability than with today's control platforms [22, 27]. It is recommended to use standard hardware in combination with virtualized software execution. Under the general condition of interoperability, docker containers makes it easy to deploy software on an edge device [23, 24].

Process and Control Visualization

Requirement: The visualization and communication of the implemented optimizations is important for the notification of employees and can be elementary for the acceptance of an autonomous system by the employees [5].

Solution component: For visualization, an HMI must usually be implemented close to the production system and connected to the edge device. If necessary, the functionality of the operational control can also be checked with the aid of an HMI and, in special cases, instructions can be given to a machine operator or maintenance personnel. [21, 28, 29].

2) *Data acquisition*

Requirements and solution components that are assigned to the data acquisition are considered in the following. It is essential to have production data available in order to identify errors and make dynamic decisions to correct them in the production process.

Data Availiability

Requirement: Continuous data availability ensures a consistent process transparency. Operationally critical as well as non-critical process and machine data have to be collected continuously in order to be able to convert each data record into a comprehensive historical and complete data basis [30].

Solution component: A short-term in-buffering of raw data serves to ensure data continuity and has to be implemented especially for cross-network data transfer. The location of the buffer must be selected centrally in the edge device and close to the data source [31].

TABLE I. REQUIRED DATA TYPES FOR PROCESSING CATEGORIES [37]

Use case	Datatype				
	MES-data	Process data	Machine data	Quality data	Logistic data
Defect detection and prevention		•	•		
Condition monitoring production process		•	•	•	
Proactive control of the production	•	•	•	•	•
Model recalculation	•	•	•	•	•

COMPREHENSIVE PROCESS TRANSPARENCY

Requirement: A comprehensive digital image of the production is required. A sufficiently large amount of data from the field level as well as the procurement of metadata from superimposed control systems are decisive for comprehensive process transparency [32].

Solution component: Different data categories and sources captures production as a whole, as shown in Table I. Depending on the application or processing type, five different data types may be used [32].

3) *Data processing*

Requirements and solution components assigned to data processing are considered in the following. Collected and stored data must be processed in the form of big data for model recalculation using data analytics and machine learning algorithms [17, 22].

SCALABILITY MODELING PERFORMANCE

Requirement: The application of data analytics and machine learning algorithms on the basis of the collected production data depends on the processing effort and the development of future resource requirements. For this purpose, an appropriate processing resource is required [17, 22].

Solution component: Cloud computing offers the advantage of simple resource scaling. A distinction must be made between a private and a public solution. A private cloud is advantageous for data with special protection and for a high model recalculation cycle on a daily to weekly basis. A public cloud is used for non-critical basic protection data and a weekly to monthly model update cycle [17].

DECOUPLING DATA STREAM AND PROCESSING LOGIC

Requirement: Connecting a variety of real-time data sources to a cloud requires centralized data capture to ensure efficient and scalable connections between local production and the cloud as the data processing and model recalculation system. Decoupling the data stream from the processing logic is essential to ensure system robustness and data processing performance [34, 35].

Solution component: An important feature of a service-orientated architecture (SOA) are separate modules that are coupled with each other via a broker. For example, if a service does not meet its response times, the broker can buffer the requests. Therefore an Apache Kafka message broker is a robust and widely used publish/subscribe (pub/sub) system that is designed for high performance in terms of message throughput and latency [35-37].

4) *Connectivity*

Requirements and solution components assigned to connectivity are considered below. Connectivity is beside control the central requirement category, since prescriptive automation requires machines, sensors and processing units to be connected and a data exchange via a variety of communication channels.

SCALABILITY AND INTEROPERABILITY

Requirement: Prescriptive automation requires a simple scalability of the IT architecture in order to adapt the ongoing interconnection and thus increasing data load with the least possible invasive methods. In addition, a growing number of different devices must be integrated through an interoperable architecture [5].

Solution component: A scalable architecture enables an increasing load by adding new hardware. This allows to constantly stabilize latency and data throughout. For this purpose, the architecture is a flexible and interoperable architecture based on modular components. The SOA is a solution for this purpose. This clear separation creates scalable system interfaces that make it possible to scale by providing an additional instance of the service when the data load is high [14, 22].

REAL-TIME CAPABILITY OF THE PHYSICAL CONNECTION

Requirement: To exchange data efficiently, communication between production hierarchies must increase significantly in order to enable prescriptive automation. The design of physical connection of sensors, machines, controllers and control systems is interoperable by a broad physical connectivity. In addition, it is essential to take real-time requirements into account. The exchange of the operational control function is subject to a hard real-time requirement, since exceeding the deadlines can have considerable consequences for the control reaction [5, 20].

Solution component: The transmission medium and data transmission protocol influence significantly the real-time capability. Hard real-time requirements usually exist for the control of machines, requiring a wired Ethernet connection to the production network. A soft real-time requirement allows wireless connection via industrial WLAN, but in this case, a wired transmission medium is usually preferable. Advantages of a wired connection are reliability and bandwidth, especially in a latency-restricted environment. In addition, in an industrial environment, wireless connections may cause interference to devices.[5, 20, 38, 39].

VERTICAL AND HORIZONTAL INTEGRATION

Requirement: A central goal of prescriptive automation is the horizontal and vertical integration of production systems and resources. Horizontal integration requires the interconnection of production systems. Vertical integration serves to connect the hierarchical levels of the automation pyramid [22, 28, 29].

Solution component: Four types of logical subnetworks allow a vertical and horizontal integration: sensor, control, compound and information networks. These networks together build a two-dimensional communication network. In the vertical direction, data can be transferred from the field level to the model recalculation in the cloud. Data is exchanged horizontally between the edge devices. The sensor network connects external sensors, whereby protocol adapter enable the connection with devices using proprietary protocols. The control network serves to connect the operative edge device indirectly via a PLC or directly to sensors and actuators. The compound network connects edge devices (C2C), which improves the interoperability of the control systems. In addition, the decentralized connection of HMIs and manufacturing execution system (MES) to the controller is made possible. The information network serves the data exchange between edge devices and the cloud [21, 22].

Interoperable Field and Control Communication

Requirement: Field and edge devices must be connected by proven industrial standard protocols in order to ensure manufacturer-independent interoperability and platform independence with regard to communication. In addition, the connection of existing devices and systems for the subsequent integration of prescriptive automation into a production system must be ensured [21, 22].

Solution component: A large number of transmission protocols exist for communication at field and control level. The protocols Open Platform Communications Unified Architecture (OPC UA) and Message Queuing Telemetry Transport (MQTT) meet the requirements for the interoperable connection of edge devices and PLCs. OPC UA is characterized by its focus on interoperability and safety aspects, its sustainability through extensions and the integrated information model according to IEC61131-3. OPC UA provides an information model for describing the data of complex systems and simplifies the connection. In addition, an OPC UA server can be integrated directly into an edge device or gateway and offers the option of buffering data for data continuity in the event of interruptions. For these reasons, OPC UA with its time-sensitive networking (TSN) and Pub/Sub extensions is recommended for connecting field devices and controllers. MQTT, on the other hand, is lightweight and optimized for use on devices with limited resources, such as low performance, low storage capacity and network bandwidths. This enables integration on small and simple sensors [40, 41].

Vertical Connection between Networks

Requirement: Field devices in the production network, the edge device and the cloud need to be able to communicate bidirectionally across network boundaries. A large number of devices must be connected centrally. In addition, compatibility with communication protocols must be ensured through the use of standard protocols for vertical data transport [41].

Solution component: A gateway is a central link that enables communication between different systems and networks. A gateway can be used between the edge device and the cloud for model recalculation as an information gateway. MQTT and HTTP are recommended as protocols for vertical transport between the edge device and the cloud, as they are the most commonly accepted protocols for vertical connections.

Data Preprocessing

Requirement: Not all data can be sensibly transported via the communication channels within and especially outside the production network. The data volume may be too large or the data content too sensitive. The amount and type of data that needs to be transported must therefore be modified by preprocessing. The requirement is not to send all generated data, but only the required and meaningful data [10, 20, 42].

Solution component: Data preprocessing is recommended in an edge device. The type of preprocessing should be based on the application of simple logic, such as checking a value change and invalid data, or on more complex data aggregation, e.g. for data reduction. This ensures that only meaningful and suitable data is transported [9, 20].

5) *Data storage*

Requirements and solution components assigned to the data storage are considered in the following. Due to comprehensive process transparency, structured, semi-structured and unstructured data must be stored and made available for application-specific processing [24].

Operational Data Storage

Requirement: The edge device unit must be able to efficiently store and manage 'active' data of operative production via real-time access [24].

Solution component: For the edge devices that sometimes have limited resources and need to store and use data reliably despite disruptions, the solution is a database system. As structured data has to be used for the operational control function, a structured query language (SQL) database is recommended. The literature recommends MySQL and PostgreSQL databases for caching metadata for the operational control function. An in-memory database realizes data storage with very low latency in industrial control systems. In this case, MySQL as relational database management system (RDBMS) is to be preferred. The storage is located in the edge device. After pushing the date to the cloud, it is important to have a cleaning process in the server to remove the daily data to prevent filling up the local storage [24, 43, 44].

Long-Term Data Storage

Requirement: A consistent long-term documentation and provision of historical data is required to generate knowledge about correlations and causes of problems for model recalculation [22, 45].

Solution component: A big data database system is required for the implementation of long-term data storage. Therefore, NoSQL databases should be used as they are able to store unstructured data sets and are very effective in terms of performance compared to relational databases. The open source database management system Apache Cassandra is best suited for use in a prescriptive automation system. [10, 46].

IV. Derivation of Reference Architectures

In this section, as shown in Fig. 2, a reference architecture is derived on the basis of requirements and solution components defined in Section III. A reference architecture forms a uniform basis for the development of system architectures with the aim of creating a common basic structure. In addition, it provides a method for moving from a general architecture to an application-specific architecture.

The following reference architecture, as illustrated in Fig. 2, is based on edge computing for operational control and cloud computing processing resources for model recalculation. The field and control layers are directly connected to the edge device. An information gateway is used for cross-network data transfer between the edge device and the cloud.

V. Conclusion

This paper presents the development of an IT architecture based on edge and cloud computing for prescriptive automation. This architecture enables network-based, interoperable process control. Furthermore, it offers the possibility of comprehensive data processing to continuously increase the productivity of the production process. We defined general requirements based on scientific publications and expert interviews. These requirements were compared with solution components. These solution components were finally combined and resulted in a reference architecture.

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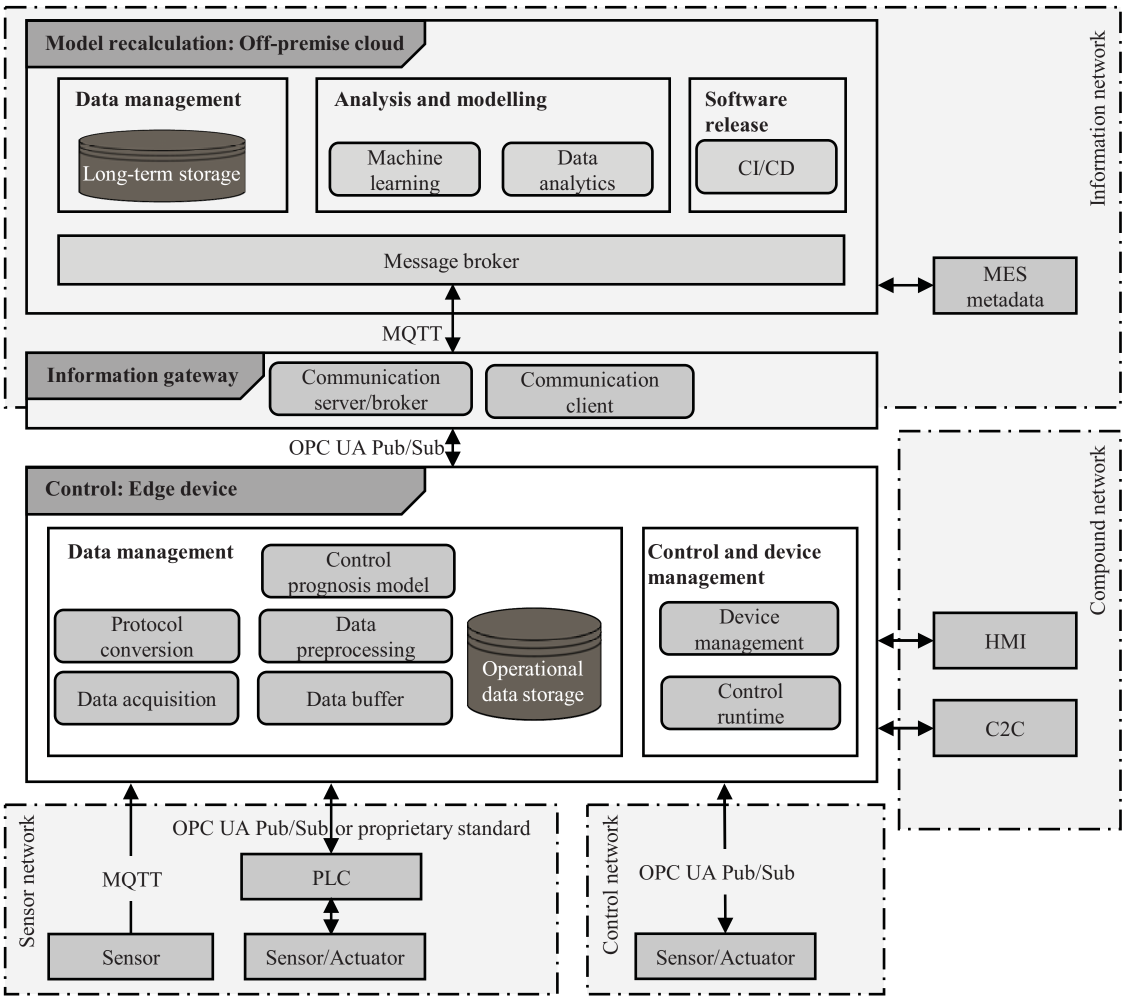

Figure 2. Derivation of reference architecture for prescriptive automation

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