An Approach for an Automated Adaption of KPI Ontologies by Reusing Systems Engineering Data

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***Abstract*—Technological progress leads to an increased utilization of data analysis and Business Intelligence that support manufacturing management decisions. Many promising solutions utilize semantic technologies. However, the deployment and maintenance of semantic technologies especially in reconfigurable manufacturing environments require a lot of manual effort. Concepts to embed them in an automated environment, as required by Reconfigurable Manufacturing Systems, are limited. In this paper, we present an approach to reuse systems engineering data to guide an automated process that updates a production data knowledge base. Thereby, an ontology that integrates distributed operational data to compute Key Performance Indicators such as the Overall Equipment Effectiveness index can be updated during the manufacturing reconfiguration process. This reduces the effort to handle the required changes of semantic data integration systems and enables a cost-effective adaption of the Business Intelligence for Reconfigurable Manufacturing Systems.**

***Index Terms*—reconfigurable manufacturing systems, semantic data integration, KPI, OEE, systems engineering**

I. Introduction

Manufacturing companies face a number of challenges these days. Globalization, shorter product as well as innovation cycle times and a growing volatility of production orders cause a change of production systems. Therefore, adaptable or reconfigurable manufacturing systems (RMS) are claimed to be key enablers for future manufacturing systems [1], [2]. They consist of intelligent and interoperable manufacturing modules that can be setup rapidly and in some cases automatically [3]. Following this concept, one challenge is the support for real-time operational decision making that is responsible to maintain and optimize the production on a daily basis [4].

Production management requires transparent knowledge of the ongoing processes. This can be achieved by utilizing Business Intelligence (BI) concepts applying Key Performance Indicators (KPIs). Therefore, data integration is required. In an RMS, this is a challenging task due to:

- frequent changes of the processes and resources,
- the variety of heterogeneous machine interfaces, proprietary protocols, and messaging structures,
- different domain-specific knowledge vocabularies.

Therefore, data integration approaches that support Business Intelligence in a reconfigurable manufacturing environment need to be investigated.

A. Related Work

Recent research has shown promising approaches to address the challenges of data integration by introducing standardized technologies, such as OPC UA and AutomationML, and utilizing semantic technologies, such as ontologies and knowledge graphs. Bunte et al. [5] introduce a semantic knowledge base to enable smart services to access data from production resources. Hildebrandt et al. [6], [7] focus on semantic modeling of knowledge in the production domain and present a method to build a respective ontology. Hästbacka and Zoitl [8] introduce a conceptual architecture and an approach to use Semantic Web technologies to self-describe the capabilities and data provided by industrial devices and control systems. Li and Niggemann [9] propose a three-layered architecture with a central, ontology-based Modeling Layer in order to address data provenance problems. Gupta et al. [10] present a system, KARMA, that utilizes mapping rules to translate structured data into RDF graphs. In order to enable an semi-automated translation process for that system, Taheriyan et al. [11] extend that approach to derive the semantic models by exploiting an existing domain ontology and previously defined semantic models of previously defined data sources. Pomp et al. [12] propose a semantic data platform, ESKAPE, in which available data are manually connected with semantic models. Thereby, the gap between isolated data silos is closed to enable an Internet of Production. In order to reduce the effort for manual annotations for that approach, Paulus et al. [13] introduce a framework to automatically recommend semantic concepts based on an algorithm that matches given labels of data attributes with semantic concepts from arbitrary pluggable knowledge bases.

The brief overview of recent research shows that semantic technologies and ontologies are utilized to enrich manufacturing data in order to increase information exchange and reduce data integration complexity. But the deployment and maintenance of these technologies still require a lot of manual effort. There hardly exist any approaches to automate this. Therefore, in this paper, we propose a concept to automatically update the required semantic models in a knowledge base by reusing systems engineering data during the reconfiguration process.

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II. Background

Business Intelligence utilizes Key Performance Indicators to gain insights into current production processes and to drive management decisions. One of the most important indicators is the Overall Equipment Effectiveness (OEE) index [14]. According to VDMA standard sheet 66412 [15], the OEE is defined as the product of a machine's *Availability (Avail)*, *Performance (Perf)*, and *Quality (Qual)*.

$$OEE = Avail \times Perf \times Qual \quad (1)$$

$$Avail = \frac{RunTime}{PlannedProductionTime} \quad (2)$$

$$Perf = \frac{RunTimePerPart \times ProducedParts}{RunTime} \quad (3)$$

$$Qual = \frac{GoodParts}{ProducedParts} \quad (4)$$

The *Availability* is the ratio between the *Run Time* when a machine performs value-adding processes and the *Planned Production Time*. The *Performance* describes the effectiveness of a machine during its run time. It is computed by the *Run Time Per Part*, number of *Produced Parts*, and the *Run Time*. The *Quality* describes the ratio between the number of *Produced Parts* and the number of *Good Parts* that meet the quality standards without any rework.

In order to compute the OEE index automatically, the respective tool needs to access the single system components and retrieve the data. Considering the provenance of the data, a brief analysis shows that the factors are distributed among the whole manufacturing system. The *Planned Production Time* is specified during production planning and stored in the respective production planning system. The *Run Time Per Part* describes the capability of machine and is stored as part of the engineering files. The number of *Good Parts*, *Produced Parts*, and *Run Time* are quantified during production and considered as operational data generated by the machine. The left-hand side of Fig. 1 shows the distribution for a single machine's setup. All operational data to compute *OEE1* are stored on the *Assembly Machine*.

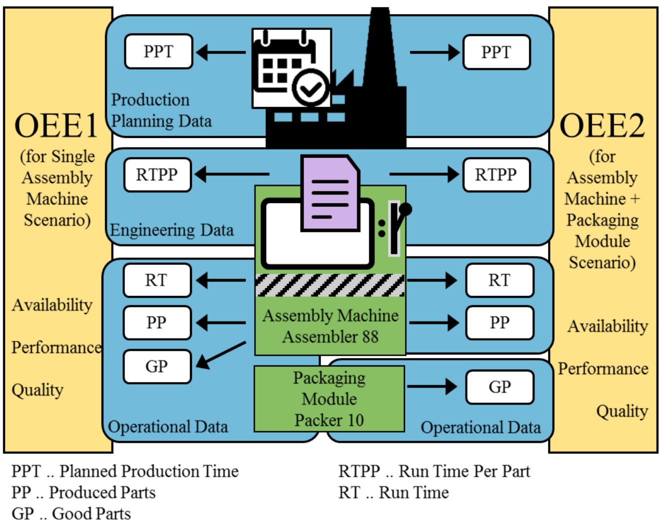

Fig. 1. Overview of the single OEE factors and their potential data sources.

A machine's setup may change frequently in a reconfigurable manufacturing environment as introduced in Section II-A. In an extended setup, the latter three OEE factors may be stored on varying data sources as shown on the right-hand side of Fig. 1. In that scenario, the number of *Good Parts*, required to compute *OEE2*, is stored on a *Packaging Module*.

Fig. 2 shows an excerpt of an exemplary ontology that represents the relationships between the three single OEE factors. They are modeled as semantic concepts that are associated with an *OEE machine* which consolidates all required data for a later computation of the OEE. The development and further introduction of such an ontology is out of scope of this paper and will be addressed in future work.

A. Application Scenario

The concept of reconfigurable manufacturing aims at increasing a manufacturer's capability to react upon changing market demands. That can be achieved by a modularization of production resources. A machine's physical as well as logical setup consists of different encapsulated modules. The machine's capability is then determined by their composition and can be changed by adding or removing those modules. For example, a machine that builds colored pencils consists of several modules that supply and assemble the single parts of a pencil such as the barrel, lid, and ink. Some customers order loose pencils, whereas others order pencils in boxes that include a specific number of pencils. Therefore, the assembly machine can be extended with a packaging module that puts the loosely produced pencils in boxes during the production process. The packaging module and assembly machine have an own programmable logic controller (PLC). A wired connection enables a data exchange between the PLCs using a proprietary interface. The respective PLC programs support a Plug and Produce approach. Thereby, the manufacturer can adapt its production resources in a fast and efficient way.

The operational data values that are used to compute the OEE index are distributed among the *Assembly Machine* and *Packaging Module*. For the single machine setup as outline on the left-hand side of Fig. 1, the *Run Time*, number of *Produced*

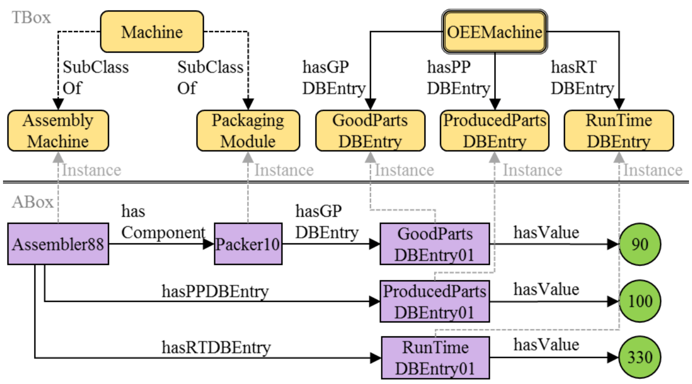

Fig. 2. Exemplary ontological representation of the machine setup for the assembly machine + packaging module scenario.

Parts, and *Good Parts* are stored on the *Assembly Machine's* PLC. In the packaging module extension setup as outlined on the right-hand side of Fig. 1, the number of *Good Parts* (boxes of colored pencils) is stored on the *Packaging Module's* PLC. In the given reconfigurable manufacturing environment, a fast and cost-effective adaption of the OEE computation pipeline is required. The integrative system component, i.e., a knowledge base, needs to have up-to-date information how to access each data source technically and process its values semantically according to the machine's current setup. Therefore, a flexible, self-adapting data integration system is required.

III. Approach

Data integration is a challenging task especially in the field of production systems due to the variety of heterogeneous machine interfaces. Proprietary protocols as well as different technologies increase the effort to implement BI use-cases. The rise of manufacturing-related standards such as OPC UA and AutomationML and their integration into semantic technologies, e.g., shown by Bunte et al. [16], facilitate the technical access and processing of machine data once a system is deployed. But setting up and adapting semantic technologies require a lot of manual effort. This is counterproductive to the main advantage of reconfigurable manufacturing systems which is *that its functionalities and capacities can be changed rapidly and cost-effectively* [4]. In contrast to approaches that utilize learning-based methods to reduce the manual effort to create and maintain knowledge bases, e.g., shown in [11], [13], our research focuses on reusing engineering data.

A. Reuse of Systems Engineering Data

Considering the whole chain of a reconfiguration process, an early phase is engineering. Here, the facility operator redesigns the manufacturing processes as well as the resources based on the engineering description of the single components. Recent research on the field of systems engineering has shown promising results to reduce the effort of system integration as well as reusing the engineering data for downstream operations. Briefly, systems engineering is an approach to support the process of developing complex technical systems by subdividing the desired system into subsystems, parts, and components and controls their implementation through all phases of the development process. Those components are described by component models that contain specific information such as the taxonomy of built-in parts, their mechanical and electrical interfaces, as well as a description of the logical behavior.

Towards our approach, we propose to extend the component models to include a KPI sub-model. The concept of the extension is shown in Fig. 3. The sub-model contains information about the operational data, as shown in Fig. 2. It holds metadata such as

- the name of the data point, e.g., **GoodPartsEntry01**
- the data point category, e.g., **GoodPartsDBEntryType**,
- the position within the machine's hierarchy, e.g., under the component **Packer10**,
- the data type and a default value.

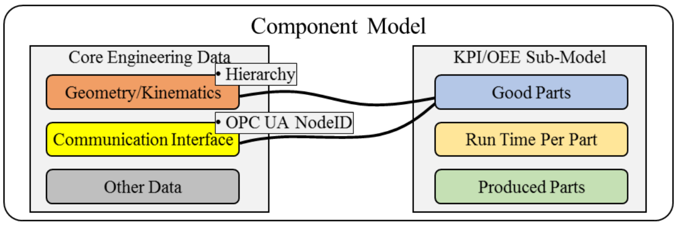

Fig. 3. Extended Systems Engineering Component Model.

That metadata catalog is pre-defined and known within the borders of the manufacturing system. Thereby, the integration of the operational data into the ontology as well as further processing is facilitated. Furthermore, the KPI sub-model is interconnected to the core engineering data of the component model, i.e., the communication interface. The communication interface holds all necessary information in order to communicate with a specific component and access the available data. For example, if a component implements an OPC UA server, the KPI sub-model would have a relation to the respective OPC UA server model that holds the browse path or NodeID of the corresponding OPC UA variable. During the reconfiguration process, that information as part of the engineering files can then be reused in order to automatically create an ontology as shown in Fig. 2.

In our previous research, we have proposed a similar approach for a maintenance use-case [17]. So in future, a component model will contain a core engineering model and several sub-models for maintenance, KPI computation etc. An introduction of a detailed KPI sub-model is out of scope of this paper and will be addressed in our future work.

B. Reconfiguration Process Steps

This section describes briefly the proposed reconfiguration process steps that are also shown in Fig. 4. A detailed implementation description of the single components of the introduced system architecture is part of our future work. Therefore, here, we will only present the general concept.

Any manufacturing reconfiguration requests are handled by experts during an engineering phase. The result of this is a factory model which contains the integrated component models of the whole plant. On the one hand, specific information from the factory model, i.e., the communication interface, is used to derive the device's communication configuration. An automatic device configuration is not part of our research. One possible implementation is shown by Wenger et al. [18]. On the other hand, the KPI model is input to a *KPI2OWL Converter*. The task of the *KPI2OWL Converter* module is two-fold. At first, it updates the ontological representation of the manufacturing system in the *Production Data Knowledge Base*. For this, mapping rules are required that rely on a system-wide, common agreement on the semantic concepts specified the component models. Secondly, the *Knowledge Base Interface Adapter* is updated as well. The adapter can be seen as a gateway between the knowledge base and the machine controllers on a shop-floor and could also perform any required preliminary processing steps before storing the

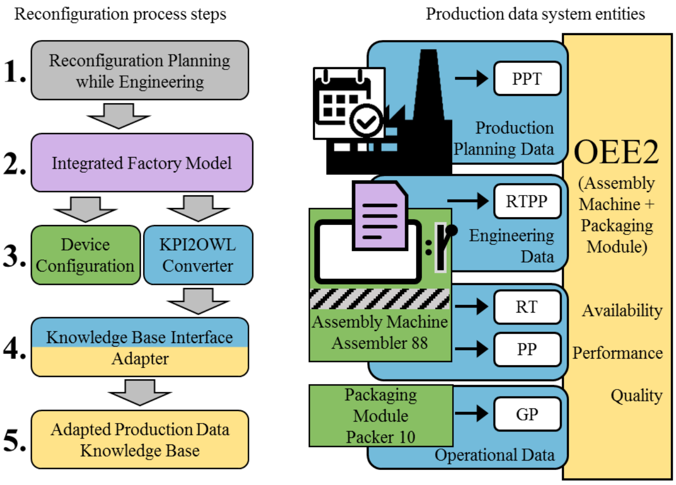

Fig. 4. Reconfiguration process steps and production data system entities.

data. With the converted information from the factory model, the adapter has all information required to access the operational data of the single devices. Eventually, the information available in the knowledge base can be further processed and queried by down-stream tools, e.g., to compute the actual OEE.

IV. Conclusion and Future Work

This paper proposes an approach to reuse systems engineering data in order to update an ontological representation of manufacturing data. Furthermore, it outlines a process for an automated approach to adapt that knowledge base. Thereby, it is possible reuse information from an engineering phase to guide the execution of manufacturing reconfiguration processes. This supports to reduce the effort that is required to deploy and maintain semantic technologies and therefore facilitates their utilization in a production environment. This is especially important for Reconfigurable Manufacturing Systems where advanced semantic data integration concepts are proposed in order to enable a cost-effective Business Intelligence.

Our future work includes an implementation of the introduced KPI model. For this, we will redefine our previous work on systems engineering component models [17] by integrating the respective sub-models. Furthermore, an implementation of the single presented reconfiguration process steps, i.e., the *KPI2OWL Converter*, is planned. For this, we will investigate and enhance previous research results e.g., presented in [19]–[21] in order to enable an evaluation of our approach in real manufacturing environments.

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