http://dx.doi.org/10.25673/116046

„Kazeem Oladipupo, Sandeep Rudra, Christian Diedrich, Sebastian Kaebisch (Hrsg.): EKA 2024 - Entwurf komplexer Automatisierungssysteme, 18. Fachtagung“

Analytics and Visualization of Industrial Asset Condition using Asset Administration Shell submodels.

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Abstract: The advent of industry 4.0 necessitates a paradigm shift toward autonomous industrial operations, prompting the integration of digital twin to orchestrate machines and processes within automation systems. The Asset Administration Shell (AAS) emerges as a pivotal digital twin intended to encapsulate an asset's lifecycle. It comprises of several submodels defining different aspects of machines or processes that in turn empowers continuous autonomy.

This potential of AAS opens the scope to extend the standardization of machine processes that are common within a factory. One of these processes is a self-diagnostic and continuous analysis of the state of a machine. This imperative not only mitigates machine downtime but expeditiously detect faults or anomalies in production processes.

This study explores the integration of Asset Administration Shell (AAS) into industrial machine analytics, aligning with Industry 4.0 paradigms. It emphasizes the application of AAS submodels for enabling machines to self-diagnose and continuously analyze their state, focusing on a universal analytics approach. This is achieved through a standardized submodel based on ISO 22400-2:2014 Key Performance Indicators (KPIs), facilitating a vendor-agnostic solution for machine analytics.

The paper highlights the effectiveness of these standardized submodels in improving machine efficiency, predictive maintenance, and operational effectiveness in industrial processes. It also discusses the challenges and practical applications of these submodels, offering insights into their real-world implementation.

Keywords: Industry 4.0, Asset Administration Shell, Industrial analytics, ISO 22400-2, data integration.

1 Introduction

In the words of Clive Humby, a British mathematician, "Data is the new oil. It's valuable, yet if unprocessed, it remains of little use. Just like oil must be converted into fuel or plastic, data too needs to be refined and analyzed to unlock its true potential." [5]. This concept, introduced in 2006, serves as a cornerstone in the realm of data-driven approaches. In the pursuit of Industry 4.0 objectives, manufacturers globally are focusing on enhancing operational efficiency and product quality.

The adoption of Industry 4.0 is driven by the inclusion of cutting-edge technologies such as the Internet of Things (IoT), Artificial Intelligence (AI), and big data analytics. Within this framework, digital twins, facilitated through the Asset Administration Shell (AAS),

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stand out as pivotal for defining assets in Industry 4.0. The AAS, with its submodels, provides a standardized framework for capturing essential characteristics of industrial assets [6].

The impetus for this paper springs from the synergy between extensive manufacturing knowledge and the innovative potential of Industry 4.0 technologies. The research aims to delve into the capabilities of the AAS and leverage the power of its submodels to bolster analytics capabilities, offering standardized descriptions for analytical KPIs. This endeavor seeks to bridge the gap between the abundance of available data and the extraction of practical insights. It advocates methodologies for depicting analytical KPIs and storing these within the AAS.

The structure of this paper is organized by beginning with the introduction which explains addresses potentials of data driven application and AAS, Section 2 presents a brief background on key topics central to the paper. Section 3 provides related work which review existing literature in area of analytics. Section 4 investigates proposed methodology for implementing the findings. It describes an analytical framework for defining KPIs within AAS and industrial analytics domain. Section 5 provides details about the implementation of the proposed methodology. Section 6 discusses some findings and provides recommendation. Section 7 concludes the paper and summarizes the research.

2 Background

2.1 Asset Administration Shell

The AAS [1] is a core element in the concept of the I4.0 Component, as evident from the AAS's definition. According to Plattform I4.0, an I4.0 Component is "*an entity with a global unique identifier and communication abilities, comprising an administration shell and an asset in an I4.0 system, offering services with specified QoS (quality of service).*" [7].

Grasping the connection between the I4.0 Component and the AAS in the context of manufacturing and Industry 4.0 requires certain critical insights. Hoffmeister underlines the crucial role of the I4.0 Component in the development of Smart Factories, marking its importance [8]. Cyber-Physical Systems are recognized for their amalgamation of the physical and digital realms. The Asset Administration Shell (AAS) symbolizes the digital facet of a CPS. Within the framework of Industry 4.0, it functions as the interface that connects the physical and virtual worlds.

The metamodel of an AAS is defined to contain collection of *submodels* which defines different aspect of the asset. in the submodel, is collections of *submodelElements* (SME). Some type of SMEs are submodelElementCollection(SMC) *property, range, submodelElementList(SML), referenceElement, etc.* in this paper, SMC and SME will be used to denote submodelElementCollection and other submodelElements types respectively.

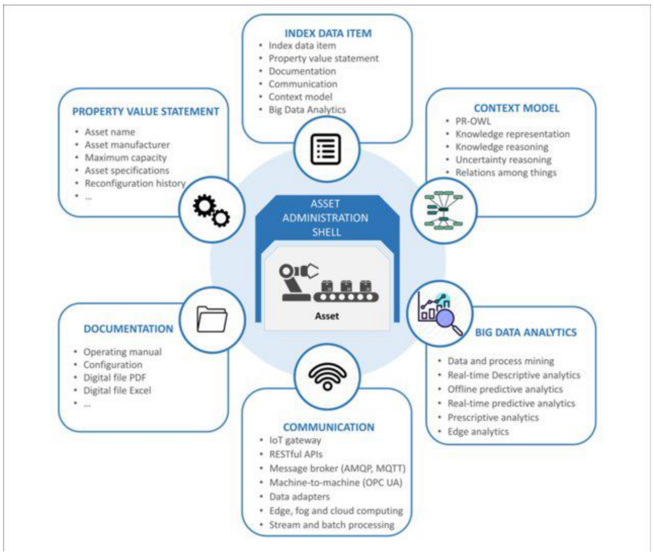

Figure 1: The role of AAS in I4.0 [9].

The AAS exist in three distinct types each offering different levels of complexity and interactivity.

The Type 1 AAS are the most basic form. They are essentially serialized files, often in formats like XML or JSON. These shells contain static information about the asset, which doesn't change over time [10]. The Type 2 AAS represent a more dynamic and interactive category. Existing as runtime instances, they are hosted on servers and can contain both static and dynamic information [10]. The Type 3 AAS are more intelligent type of AAS built on type 2 AAS to be autonomous and have decision making capabilities. They can interact with other AAS using industry 4.0 language.

2.2 Overview of Industrial Analytics

The manufacturing sector worldwide is experiencing a profound shift moving from traditional physical production to focusing on data-driven processes and products. This digital shift is creating vast amount of diverse data throughout the industrial value chain, ranging from simulation data in the design phase to sensor data during manufacturing, and sensor data during the usage of the product therefore huge amount of data is generated during the complete life cycle of a product, encompassing all stages from initial design to eventual recycling. Gaining valuable insights and knowledge from this data is becoming a crucial factor for success in the industry, such as for process optimization and product enhancement [11]. This process is known as industrial analytics, which involves applying data analytics specifically for generating industrial value. Sitting at the intersection of data science and industrial engineering, industrial analytics is fundamental to Industry 4.0 [12].

The phrase "industrial analytics" typically denotes the use of data analytics for generating value in the industrial sector, often in the context of Industry 4.0. It's also interchangeably referred to as "Industry 4.0 analytics “and "industrial intelligence". Common form of analytics are descriptive analytics, diagnostic analytics, prescriptive analytics, and predictive analytics [13]. Table 1 shows the focus and basic analytic question attached to these analytics types.

Table 1 : Types of Analytics and their focus areas

	Descriptive Analytics	Diagnostic Analytics	Predictive Analytics	Prescriptive Analytics
Focus	Transparency	Root Cause	Forecast	Action
Analytical Question	What has happened? What is happening?	Why has it happened?	What will happen?	How can we make it happen?
Example	What is the current first pass yield (FPY)?	What has decreased in certain regions?	What will be FPY in the next quarter?	How can we increase FPY?

3 Related Work

Predictive Maintenance (PdM) plays a crucial role in the framework of Industry 4.0, particularly within the context of smart manufacturing. The AAS is suggested as an essential element in attaining interoperability and reducing the complexity of operational technology. This is crucial for harmonizing various PdM strategies in the ever-changing industrial sector [14] [15]. An important aspect of authors research is a case study that examines the application of machine learning in predictive maintenance (PdM) of milling machines. This case study demonstrates the practicality of the methodology by using data from diverse sources to perform predictive analytics. The model’s potential in various industrial applications and its effectiveness in solving real-world difficulties are highlighted by these practical demonstrations [14][15].

The development of ISO 22400 was driven by the need for a standardized approach to performance measurement in the manufacturing industry. Prior to its introduction, manufacturers often relied on a variety of inconsistent and non-comparable metrics to assess their operations. This lack of standardization led to significant challenges in benchmarking and optimizing performance. In response, ISO 22400 emerged, providing a structured and universally applicable set of KPIs. These KPIs align with the evolving needs and technological advancements in the manufacturing sector, offering a solution to the previously fragmented approach to performance measurement. The standard’s development also reflects a growing trend towards globalization in manufacturing, necessitating a common framework that can be applied across diverse manufacturing environments [3]

The discussion of ISO 22400[3] is pertinent as this standard provides the framework for defining analytical KPIs in the context of the analytic submodel. This standard is instrumental in establishing a structured approach for the description of key performance indicators, thereby facilitating a standardized and coherent method for developing the analytic submodel.

4 KPI description with AAS submodel

In the context of AAS, the overall architecture used in this paper is provided in Figure 2. In this architecture is an AAS server hosting a type 2 AAS. This AAS contains some submodels that collaborate to provide an analytics value for the machine user. The analytics submodel is the focus of this paper. Other submodels shown in Figure 2 are in one way or the other helping the analytics service (Analytics App) to carry out its function real-time and on-demand.

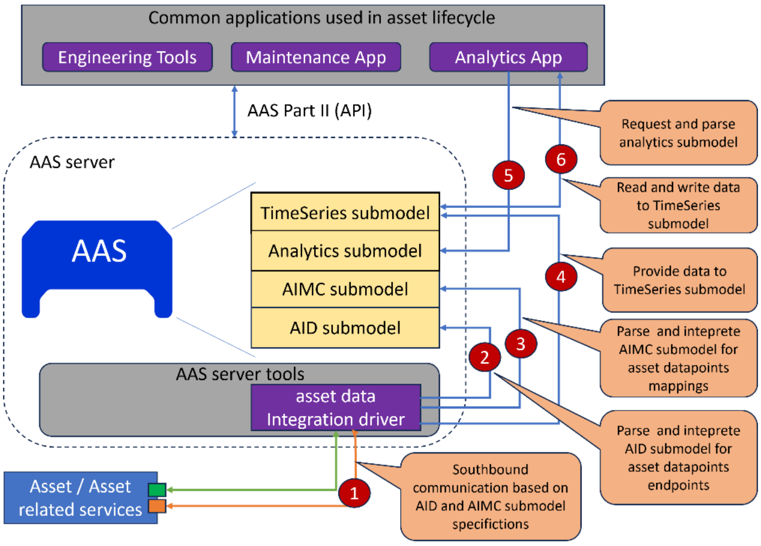

Figure 2: Proposed methodology.

4.1 Analytics Submodel

Providing a top-down mapping of the KPI structure provided in ISO-22400[3] into analytics submodel. As seen in Figure 3, the Top SMC defines the name of the KPI and inside the SMC, other information related to the KPI is provided. The *Datapoints* (an SMC containing Reference SMEs) and *Value* (a Reference SME) are extension of the original KPI structure. They are used to provided references to parameters used in calculating KPIs and storing the calculated outcome respectively.

Other information in the *KPI* SMC are used by the analytics service as a guidance on how the calculation will be performed. For example, the *Timing* SME can define if a KPI should be calculated in real-time, periodically or on-demand. The Rating SME tells the upper and lower limits trend of the KPI.

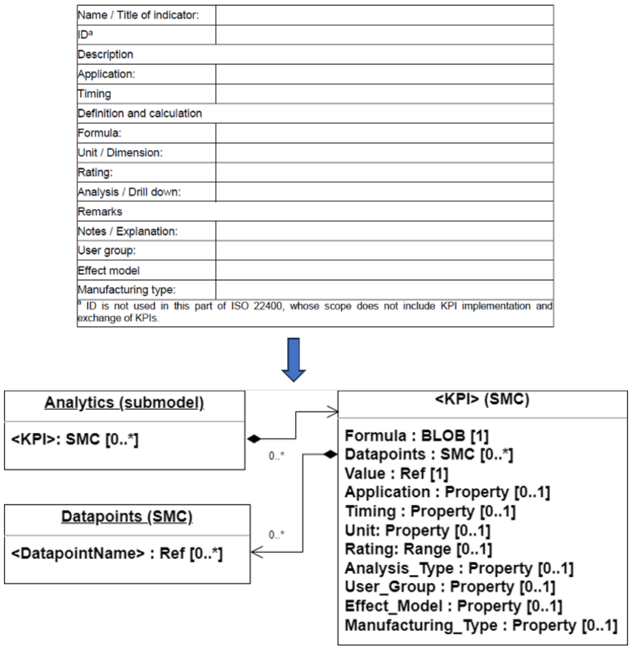

Figure 3: Mapping of ISO 22400 KPI structure into Analytics Submodel UML

4.2 Asset Interfaces Description (AID) and Asset Interfaces Mapping Configuration Submodels (AIMC).

The AID [4] and AIMC submodels shown in Figure 2 helps the AAS integrate its corresponding asset’s operational data. The AID submodel contains description of interfaces related to asset datapoints and/or related services and AIMC provides mapping of asset payload to a designated location within the AAS.

Since all the metrics needed to calculate a machine KPI are all time dependent information, bringing them into the AAS needs to be defined as time dependent parameters. The *TimeSeries* [2] submodel offers such possibilities. The *TimeSeries* submodel allows AAS elements to be recorded with respect to the time.

This paper combines the potentials of already defined submodels like *TimeSeries* submodel, AID and AIMC submodel to achieve its analytics goal.

5 KPI implementation with AAS analytics service.

This chapter focuses on the implementation of the submodel modelled in section 4. This implementation consists of two interconnected parts: The development of an AAS with necessary submodels as seen in Figure 2 and the integration of analytical service as a proof of concept to the potential of analytics submodel. The metric that would be focused on this development is the *Overall Equipment Efficiency* (OEE).

5.1 AAS and Submodels Development:

Leveraging the AAS package Explorer, the AAS and its submodels are developed to encapsulate all the core aspects of an asset. Amongst these aspects is the asset's operational metrics. The *OEE* is one of the important metrics used to evaluate how well a machine is operating with respect to its expected production output. To evaluate a machine's OEE, metrics like *availability*, *quality* and *performance* of the asset is captured or calculated. Figure 4 shows the overview of an asset's AAS containing the analytics submodel where holds the descriptions of some KPIs used to evaluate the machines overall efficiency.

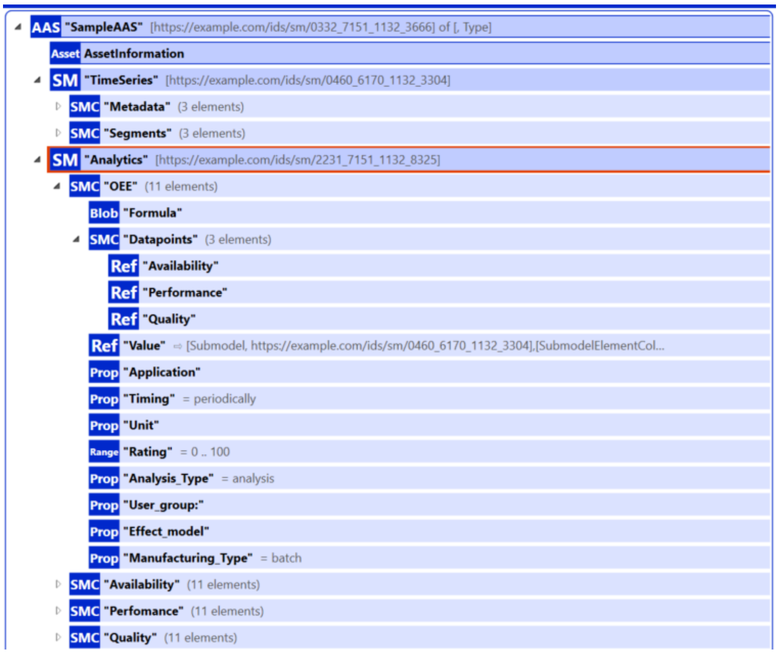

Figure 4: Sample AAS with Analytics Submodel as described in section 4 and Figure 3

As seen in Figure 4, the Formula (BLOB SME) contains the formula for the OEE in a blob format and the datapoints SMC provides references to the parameter to be used in the formula. For this implementation, the datapoints are time-based metrics so they are provided in the *TimeSeries* submodel and referenced in each metrics (Availability SMC, Performance SMC and Quality SMC) datapoint. The value of the calculated OEE is also provided in the *TimeSeries* submodel because it is a time-based metric.

The OEE which is a well-known KPI in manufacturing, combining availability, effectiveness, and quality ratio. It shows the percentage of productive manufacturing time. A perfect OEE score of 100 percent means manufacturing high-quality parts efficiently and without stoppages. OEE is ideal for improving equipment productivity, identifying losses, or benchmarking performance. It is calculated with the following formula:

$$OEE\ Index = Availability * Quality\ ratio * Performance\ [3]$$

5.2 Analytic Service

The analytic service uses the AAS analytics submodel to run analytics on an AAS specific to an asset. Figure 2 shows the overall picture of how the analytics service is implementated.

The flowchart of the analytics service is provided in Figure 5 considering that AAS server is running, and asset data integration driver shown in Figure 2 is integrating asset datapoints into the AAS. The flowchart serves as a guide to the systematic process the analytic service implementation, detailing each step from data input to processing and output.

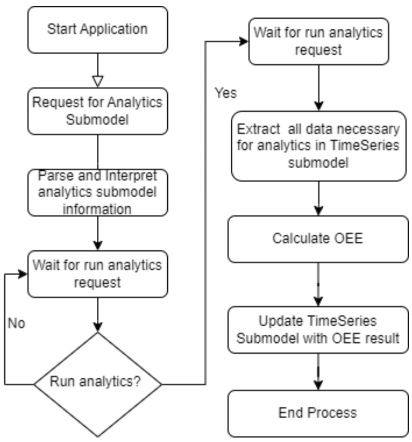

Figure 5: Flowchart for analytics service.

6 Discussion and Recommendation

During the development of the analytics submodel, it was seen that the TimeSeries submodel is an important submodel for its implementation because that is the only submodel that stores time-related data within AAS ecosystem.

One of the drawbacks of the *TimeSeries* submodel is that it is structured to store collection of data within one time stamp. The metadata SMC does not allow the creation of multiple records for different data collection. For instance, asset datapoints or asset related services data can be created with one record and an opportunity to create another record that is not specific to asset datapoints.

It is recommended that this feature is investigated because if AAS will capture different aspects of asset information across its life cycle, it is certain that some of these aspects might need TimeSeries submodel at different time by different applications.

The *analytical* submodel is an ideation of how asset analytics can be achieved with AAS. There is still some work to be done on the modelling most especially on the Formula SME. some rules on how the expression will be presented must be defined for all users to know how to property provide their formulas.

Also, because the formula SME is using BLOB, the information provided in the BLOB needs to be properly and intelligently interpreted by analytics service according to the expression rules.

7 Conclusion and Outlook

This paper has provided a review of fundamental elements of Industry 4.0, specifically emphasizing on the Asset Administration Shell (AAS) and its use in the domain of industrial analytics. As industrial automation technologies continue to advance, the importance of on-the-fly analytics that can be used to evaluate assets is paramount. Providing a standardized description for well-known KPIs to enable *plug-and-analyze* capabilities for applications on the shop floor will help facilitates early detection of problems in machines.

The proposed methodology aligns with current Industrial approach for implementing the AAS. The methodology architecture has been designed to create a connection between *Analytics*, and *TimeSeries* submodels, with each submodel serving a distinct function in the asset. The method included the process of defining asset datapoints in AID and AIMC submodels that facilitates data integration from asset.

The implementation section provides an overview of how the proposed methodology was implemented. This involved the development of the AAS and its submodels using the AASX Package Explorer, defining important KPIs and their parameters, which are then used by analytical services.

Though the analytics submodel in this paper focuses on assets KPIs. In future work, an extension of how this submodel can be used to analyze a part (component) of asset from the information provided in either the asset's PDF manual or *TechnicalData* submodel with the use of technology like Large Language Models (LLMs) is expected to be explored.

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