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Perspective

Digital Representation of NDE Systems: Data Networking and Information Modeling †

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Abstract

To enhance the measuring capabilities of modern Non-Destructive Evaluation (NDE) devices, it has become essential to integrate standardized digitization services and industry-compliant functionalities. This perspective paper examines approaches for improving NDE systems by incorporating key Industry 4.0 technologies, specifically digital representations such as the Asset Administration Shell (AAS) and OPC UA (Open Platform Communications Unified Architecture). We discuss requirements for interoperable, semantically rich descriptions of NDE systems, outline how OPC UA information models and AAS submodels can be combined with MQTT-based transport, and illustrate these concepts through representative prototype implementations, including predictive maintenance and chatbot assistant use cases. By leveraging these technologies, NDE devices can be transformed into interoperable, data-rich, and intelligent components within smart industrial ecosystems. Compared with previous studies, this Perspective is the first to systematically bring together the requirements, architectural patterns, and evaluation criteria for digital representations designed specifically for NDE systems. It also provides, in a practical and accessible way, NDE-focused OPC UA and AAS-based architectures that support both predictive maintenance and LLM-assisted operator guidance. The presented implementations are at an early stage and serve as illustrative examples, while systematic quantitative validation is ongoing and is outlined as future work.

Keywords: NDE systems; digital representation; digital twins; smart manufacturing; OPC UA; MQTT; Asset Administration Shell

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1. Requirements for Digital Representations of NDE Data and Systems

Digital transformation and Industry 4.0 place increasing demands on the integration and interoperability of Non-Destructive Evaluation (NDE) systems. While NDE devices are widely used as critical data sources in manufacturing, their integration into Industrial

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Internet of Things (IIoT) environments is often based on proprietary interfaces and heterogeneous information models. This limits cross-vendor interoperability, complicates system integration, and hinders the deployment of advanced data-driven services such as predictive maintenance and intelligent assistance. At the same time, there is no widely adopted, domain-specific guidance on how to leverage digital representation technologies such as OPC UA, the Asset Administration Shell (AAS), and MQTT specifically for NDE applications.

An important requirement of digitalization is the availability of relevant information through suitable systems and devices [1–3]. This concerns not only the intelligent participants in a network, but also the way shared information is represented and structured. To understand current requirements, it is helpful to recall the network structures of the third industrial revolution regarding automation and IT, which remains universal in many factories. At that time, production systems upgraded from manual assembly units to automated and robotic solutions. At the same time, communication technologies were introduced to manage manufacturing processes, which led to hierarchical communication structures as depicted by the automation pyramid [3,4].

For different real-time and data volume requirements, the automation pyramid separates processes and data flows into several levels. For instance, the actuator-sensor level requires “hard” real-time responses within milliseconds, while the ERP level requires “soft” real-time responses which could take up to minutes or even hours. At the start of the fourth industrial revolution (Industry 4.0), this simple structure is still widespread, although it also presents new challenges: When subsystems use different protocols or inconsistent data formats, how can they communicate at the same level of the hierarchy? These problems were frequently avoided by using controllers as central interfaces rather than direct data interchange [5]. Additional connections were established if necessary. Though, these approaches now conflict with the objectives of Industry 4.0 and IIoT networks, which demand adaptable, direct information sharing across all network users. To address this, tightly coupled and diverse communication topologies of the automation pyramid are increasingly being replaced by service-oriented architecture (SOA) [6]. SOA is an infrastructure for structuring and using distributed capabilities, potentially under multiple ownership domains, according to OASIS [7]. Ideal services within SOA should:

- Be self-contained and independently usable;
- Be available over a network;
- Have a clearly defined, published interface;
- Be platform-independent;
- Be registered in a directory and discoverable;
- Support dynamic usage.

These requirements are rarely entirely met, which creates new difficulties for developers integrating systems into IIoT networks. Manufacturer-specific solutions give way to standardized communication technologies and the requirement for semantic data representation due to factors including network availability, defined interfaces, and platform independence. Additionally, technical requirements must comply with legal frameworks like the EU Data Act [8]. This regulation requires manufacturers to make product and service data accessible to ensure interoperability between different systems and services. Therefore, standard protocols and data formats are necessary to enable seamless data exchange within SOA. These requirements are also applicable to the integration of non-destructive evaluation (NDE) procedures and systems.

It is not very difficult to provide a single procedure as a service. Several modern NDE technologies, such as thermography, eddy current, and ultrasound, already have network interfaces and can be used independently as closed systems that can be semantically defined.

Therefore, even though standardized semantic representations are currently absent, the technological requirements for IIoT integration are usually present [9–11]. Other methods, such as dye penetrant testing, require manual operation and therefore need dedicated digitalization strategies. The goal is to digitally represent them as service-oriented solutions and not just automate manual processes. Both the variety and degree of automation of NDE systems must be considered for this. The following conditions must be fulfilled to successfully integrate NDE systems into an IIoT network using SOA principles:

- Uniform semantic description of different NDE systems;
- Representation as independent, self-sufficient usable services;
- Digital representation of manual processes;
- Consideration of the degree of automation;
- Seamless communication between different systems;
- Clear identification.

Careful standardization and adherence to current standards are necessary to meet these goals. At the same time, there are significant standardization difficulties with digital representations. High integration costs and the possibility of semantic misunderstandings are caused by heterogeneous, manufacturer-specific models, unclear versioning, and a lack of backward compatibility in proprietary models. Implementation is additionally hindered by organizational obstacles related to roles, governance, procurement, data sovereignty, security/compliance, and fragmented interfaces. To address these challenges requires harmonized base models with expandable submodels, precise rules for further development of the models, and formal proof of conformance with the help of certification and reference implementations. Additionally, scalable solutions require quantitative validation. This could be evaluated with an interoperability score, integration effort, robustness, performance, and semantic coverage. However, there is a clear requirement for digital representations in NDE, because accurate and detailed digital representations form the base for precise, interoperable descriptions and make NDE techniques ideal data sources for IIoT networks. The following chapters depict suitable technologies and real-world applications that address these requirements.

Despite active research on NDE 4.0 and digital twins, the literature still lacks a consolidated view on requirements, architectural patterns, and evaluation criteria for digital representations tailored to NDE systems. In this work, we adopt a conceptual and architectural perspective on the digital representation of NDE systems rather than presenting a fully validated solution. Building on our previous study [12], we (i) consolidate current requirements for digital representations of NDE data and systems, (ii) survey relevant enabling technologies (OPC UA, AAS, MQTT) with a focus on their interplay, and (iii) present representative prototype implementations from ongoing research projects as illustrative case studies. The paper does not yet provide comprehensive quantitative validation of these implementations. Instead, we outline planned evaluation strategies and discuss technical and organizational challenges that need to be addressed before broad industrial adoption.

The objective of this Perspective is to provide structured guidance on how to design and implement interoperable, semantically rich digital representations for NDE systems using OPC UA, AAS, and MQTT. We address the following guiding question: How can digital representation technologies such as OPC UA, the Asset Administration Shell, and MQTT be combined to realize NDE systems that are interoperable across vendors and that effectively support predictive maintenance and intelligent assistance?

The remainder of this Perspective is structured as follows. Section 2 reviews state-of-the-art technologies for digital representations and their relevance for NDE. Section 3 discusses the development of OPC UA Companion Specifications for NDE and analyzes associated standardization and governance challenges. Section 4 describes the role of

MQTT as a transport layer for digital representations in resource-constrained scenarios. Section 5 presents two applied architectures based on the Asset Administration Shell: a predictive maintenance use case in additive manufacturing and a conversational assistant for NDE support. Section 6 concludes the paper by summarizing key insights, limitations, and directions for future work.

2. State-of-the-Art Technologies for Digital Representations

To describe systems with an IIoT network requires a clear digital representation [13]. This encapsulates how data, information, and concepts are presented and processed in a digital format, which enables digital devices to efficiently store, analyze, and transmit data. The relevance and complexity of digital representation increase as advancements in technology take place, creating new challenges and opportunities for both research and industrial domains.

The terms Digital Representation and Digital Twin are often used interchangeably in this context, although they address different aspects. Digital representation mainly refers to a machine-readable, semantically described image of a physical or virtual asset [14]. On the other hand, the digital twin itself is described as a continuously synchronized, rich in context digital representation of a physical system throughout its entire life cycle [15]. In this Perspective, we use “digital representation” as an umbrella term for machine-readable models of NDE systems, and reserve “digital twin” for those representations that are continuously synchronized with the corresponding physical asset over its life cycle. To implement this technically, several technologies are listed below, such as MQTT (Message Queuing Telemetry Transport), OPC UA (Open Platform Communications Unified Architecture), and AAS (Asset Administration Shell).

In an industrial context, digital representations are essential for mapping physical objects, processes, and systems in virtual environments. This mapping not only covers the static information of machines and plants, but also their dynamic properties, such as current operating states and interactions with other components. By incorporating digital representations, companies can gain valuable insights into their production systems, which can eventually support improved efficiency, quality, and flexibility. A key application of digital representation is to develop digital twins/virtual replicas of physical assets. Digital twins based on their real-time data analysis capabilities enable simulations, scenario testing, and informed decision-making. They also support collaboration between departments and stakeholders by facilitating a common, up-to-date foundation. In the NDE context, they form the basis for advanced/smart assistant systems that are relevant for manual inspection operations. For a few inspection modalities in which the data is complex and handling of sensors needs precise positioning and detection (e.g., UT [10] or 3MA [16]) such assistance could be used to improve data quality and reproducibility by reducing human factors but also help troubleshooting. Furthermore, the capability to communicate in natural language via chatbots facilitates hands-free operation for initiating measurements and modifying specific settings, which is highly valued by practitioners. Numerous essential technologies facilitate the execution of digital representations and promote secure and efficient information transmission among machines, systems, and applications. Notably, OPC UA [17], MQTT [18], and the Asset Administration Shell [19] are particularly significant. MQTT is an open machine-to-machine network protocol that functions as a lightweight message system in industrial settings. It effectively distributes data among several clients by using a publish/subscribe architecture managed by a central MQTT broker. Because of its architecture, it can be used to integrate legacy systems and devices that have limited hardware capabilities. However, there are no established semantic models or guidelines for data interpretation in MQTT. In addition, although data transfer is efficient, the meaning of the information remains system-specific and is not necessarily interoperable.

OPC UA is a commonly used industrial communication standard that offers a scalable and adaptable data exchange platform. OPC UA applications can be used on a variety of hardware and environments, such as PCs, embedded systems, and cloud platforms, due to their platform independence. Additionally, OPC UA functions as a framework across many communication interfaces and is agnostic of protocols [20]. Additionally, due to its scalability, it may be used in both large, complex automation architectures and small, isolated applications. OPC UA's hierarchical data model supports the clear representation of complex data structures. Businesses can specify data types and connections using standardized information models, facilitating integration and interoperability.

The AAS is another central technology for digital representation in the context of Industry 4.0. It offers a standardized digital description of physical or digital assets and is characterized by the Industrial Digital Twin Association (IDTA) as a universal form of digital twin [19,21]. Within the AAS, information is structured into submodels that specify an asset's properties and functionalities. This organization facilitates consistent data exchange and interoperability across heterogeneous systems and manufacturers, thereby easing integration across different platforms. The values managed by an AAS can be retrieved either offline as separate instances or directly from the corresponding asset. While the AAS does not prescribe a particular communication protocol, it frequently operates in conjunction with middleware solutions such as BaSyx, which may themselves rely on OPC UA [22].

Although OPC UA and AAS have similar objectives, their focal points are different. OPC UA emphasizes interoperability and communication framework more; on the other hand, AAS focuses on semantic data modeling. Both technologies can be used together: for example, semantic models and functions can be mapped from AAS to OPC UA communication structure [23]. This integration provides comprehensive and interoperable data exchange.

All three technologies, MQTT, AAS and OPC UA are important in the context of Industry 4.0. Each serves different purposes: MQTT is best-suited for lightweight, resource-oriented systems, OPC UA delivers robust, standardized communication and data modeling, and the AAS is well-suited for modeling semantic digital representations. The upcoming sections will primarily focus on OPC UA and AAS, since they are suitable for complex, semantically rich digital representations in NDE applications.

Existing NDE 4.0 and digital twin literature (e.g., refs. [4,9–11,16]) highlights the potential of IIoT integration, cognitive sensor systems, and digital twins for inspection processes, but typically focuses either on specific sensor technologies or on high-level conceptual visions. In contrast, comparatively few works address concrete architectural patterns, standardized digital representations, and evaluation criteria for integrating NDE systems with OPC UA, AAS, and MQTT in a systematic way. This Perspective therefore complements the existing literature by focusing on the design of interoperable digital representations and their realization through standardized industrial technologies in NDE-specific use-cases.

Comparison of Digitalization Approaches for NDE Systems

While a variety of technologies can be used to digitalize and integrate NDE systems, they differ significantly in terms of semantic richness, standardization maturity, and suitability for heterogeneous industrial environments. Table 1 summarizes key characteristics of commonly used approaches.

Table 1. Comparison of Standard Interfaces.

Approach	Semantic Modeling	Standardization Maturity	Suitability for Brownfield/Edge	Typical Interoperability Level
Proprietary interfaces/REST APIs	Low–medium	Vendor-specific	Medium	Limited to vendor ecosystem
MQTT with ad hoc payloads	Low	MQTT protocol standardized, semantics ad hoc	High (lightweight)	Low; semantics not standardized
OPC UA	Medium–high	High (OPC UA + Companion Specs)	Medium	High within OPC UA ecosystem
AAS	High	Emerging (IDTA submodels, AAS spec)	Medium	High for AAS-compliant assets
OPC UA + AAS (this work)	High	High (OPC UA) + emerging (AAS)	Medium–high (via OPC UA and MQTT)	High, with both standardized comms and rich semantics

The combination of OPC UA and AAS, optionally transported via MQTT, offers a pragmatic compromise between semantic expressiveness, implementation effort, and compatibility with existing industrial infrastructures. OPC UA provides a robust and widely adopted communication framework and information modeling capabilities, while the AAS adds a standardized, extensible semantic layer suitable for representing complex NDE systems across their life cycle. This combination is therefore particularly attractive for NDE digitalization, where multi-vendor interoperability and semantically rich descriptions of inspection systems and results are crucial.

3. Development of Standard OPC UA Information Models in the Context of NDE

A key step in implementing OPC UA in NDE systems is the development and implementation of Companion Specifications. These specifications facilitate standardized, semantically described processes, which enable interoperability between various systems and stakeholders. These companion specifications are information models created by expert working groups within the OPC Foundation, bringing together industry and academic stakeholders to develop collaboratively. Currently, Joint Working Group Non-Destructive Evaluation (JWG NDE) is developing a Companion Specification specifically for NDE systems. The goal is to develop a model which addresses the unique requirements and challenges of NDE technologies and to support their seamless integration into digital production environments. However, this model needs a certain balance between addressing general challenges common to all NDE procedures, and it is not feasible to cover every specific detail of all diverse NDE methods in a single model.

Two strategies are used to overcome this. First, Companion Specifications are designed flexibly and are updated on a regular basis to remain up-to-date and adaptable. Second, users can extend the standard information models with custom, application-specific extensions as needed. Therefore, the JWG NDE aims to develop a generic information model that fits the fundamental aspects of NDE, which can then be complemented by specific submodels for individual use cases or technologies. The goal of the proposed information model is to digitally map each phase of the NDE process, from obtaining the inspection order to reporting the results of the evaluation as shown in Figure 1. The management of inspection instructions, the explanation of test systems, and the representation of results from inspection are some of its components.

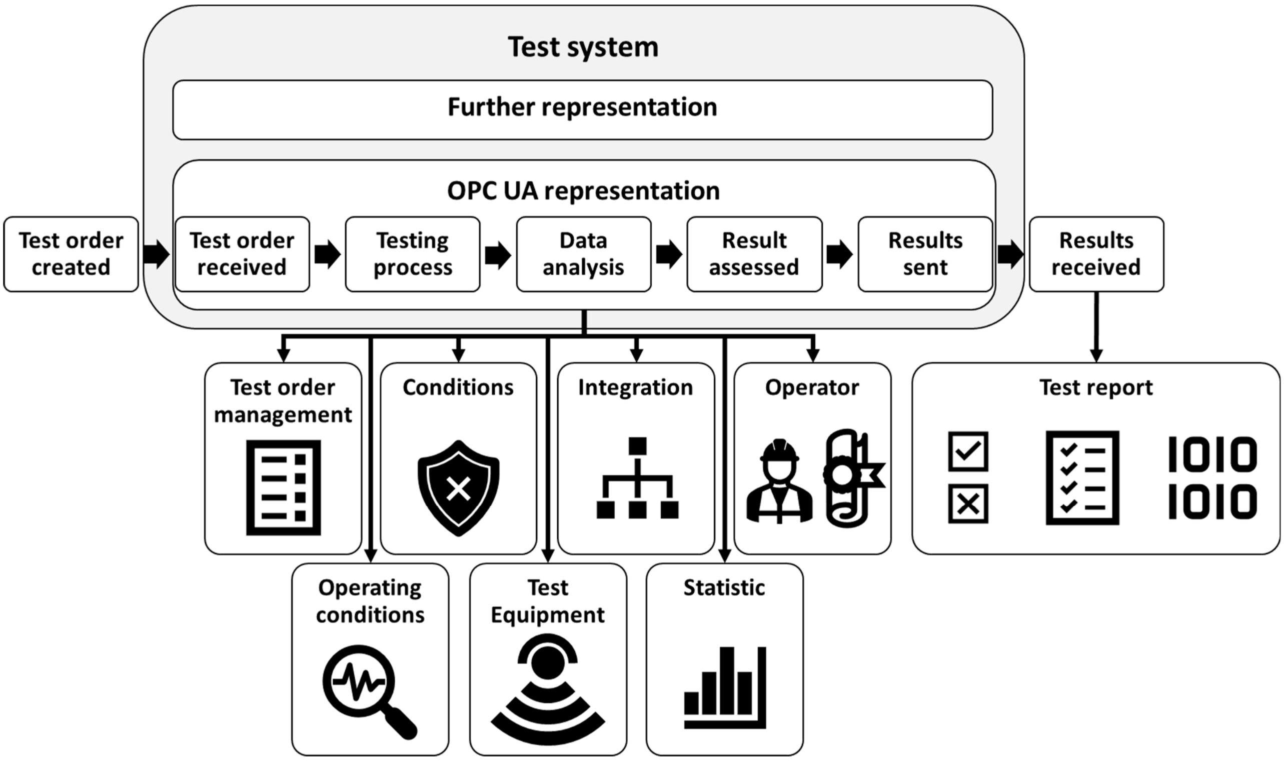


Figure 1. Current graphical representation of the addressed scope of the information model of the Companion Specification of OPC UA for Non-Destructive Testing—Part 1: Testing System.

Although a conclusive Companion Specification for NDE systems is not currently accessible, OPC UA can already offer considerable advantages. The deployment of the OPC UA framework is dependent upon the current hardware interfaces. Established interfaces like PROFINET, Ethernet/IP, EtherCAT, or basic TCP/IP can be converted into distinct OPC UA models. Moreover, other OPC UA Companion Specifications may provide a basis. For instance, VDMA 40100-1 "OPC UA for Machine Vision—Part 1: Control, Configuration Management, Recipe Management, Result Management" is especially suitable for image-based NDE processes.

Real-world examples of OPC UA in NDE systems are already found in both research and industrial applications. For example, OPC UA is utilized in the nexAMo research project [24] to link NDE processes in a flexible digitalized matrix production setting. With all data controlled and stored automatically via OPC UA, the goal is to create a compact computed tomography (CT) system that can scan detail areas based on digital instructions and provide test reports in accordance with digital requirements.

At Fraunhofer IZFP, OPC UA enables the integration of systems into production lines and fulfills key Industry 4.0 requirements. The inspECT-PRO platform for eddy current testing uses OPC UA to perform automated sorting inspections for the detection of material defects and the evaluation of mechanical properties. For this purpose, a dedicated OPC UA information model was implemented [25].

In summary, standardized OPC UA information models, particularly those based on Companion Specifications, are a central enabler of interoperability and flexible integration of NDE systems in digital production environments. Although work on a comprehensive NDE Companion Specification is still in progress, existing standards and custom extensions already deliver substantial benefits and viable practical solutions.

A central challenge in applying such an information model lies in reconciling cross-process generality with the application-specific depth required by NDE use cases. One proposed approach is to employ the generic base model presented here and augment it with supplementary submodels that provide technology-specific extensions. However, this approach also introduces the risk of fragmentation and rising integration costs if profiles, clear versioning schemes, backward compatibility, and binding conformance tests are not established. While deterministic inventory protocols such as Profinet can be mapped relatively straightforwardly, dynamic interfaces and resource-constrained devices demand additional semantic enrichment, which may increase the likelihood of misinterpretation and the associated integration effort. The long-term sustainability of semantic models depends on robust governance of Companion Specifications and requires regular maintenance, harmonization, and well-defined migration paths to prevent lock-in effects, ambiguous semantics, and elevated operating costs. Furthermore, cybersecurity considerations must be addressed: although OPC UA incorporates TLS, authentication, and authorization mechanisms, it simultaneously increases the potential attack surface due to heterogeneous architecture involving gateways and pub-sub topologies. Consequently, for broad industrial adoption, binding core profiles, legacy migration strategies, practical security patterns, and stringent conformance testing are essential complements to the base model.

4. MQTT as a Transport Layer for Digital Representations in NDE

MQTT can be used as an efficient transport layer for digital representations of NDE systems, especially in edge or brownfield scenarios where devices are resource-constrained or operate on low-bandwidth networks. In MQTT, communication between different devices or clients takes place via a broker, which reduces communication overhead and decouples data producers from data consumers, making it a lightweight messaging protocol. However, MQTT itself does not define any information model or semantic layer. Topic hierarchies and payload structures are left entirely to the application, which often results in heterogeneous, system-specific encodings and limited interoperability [17].

To address this semantic gap, MQTT-based NDE systems can align their topic structures and payload schemas with established information models, such as OPC UA Companion Specifications or AAS submodels. One practical approach is to serialize AAS submodel elements (e.g., inspection parameters, operating states, anomaly events) into JSON or binary payloads and publish them on well-defined MQTT topics that reflect the AAS structure. In this setup, the AAS remains the canonical digital twin, while MQTT serves purely as the transport mechanism [18,22,26]. Similarly, OPC UA Pub/Sub bindings over MQTT or MQTT-SN make it possible to transmit standardized OPC UA datasets via MQTT, combining MQTT's simplicity with the rich information modeling and security features of OPC UA [19].

5. Development of Asset Administration Shells for NDE Applications

Although OPC UA and the Asset Administration Shell are both central technologies for semantic description and interoperability, they follow fundamentally different paradigms. OPC UA information models are generally developed by expert committees and standardized in the form of Companion Specifications. By contrast, AAS submodels are frequently defined by end users or independent organizations to address specific application requirements. These submodels can be published and made available via the Industrial Digital Twin Association (IDTA), where each model is subjected to an evaluation process and may be iteratively refined. This procedure ensures interoperability through the AAS framework itself, while simultaneously permitting flexibility and adaptation to individual requirements.

In the context of NDE systems, this implies that application-specific requirements take precedence. The review and reuse of existing, published submodels can substantially reduce the effort required for implementation. AAS submodels offer detailed, structured representations of various asset-related aspects, making them particularly suitable for capturing the heterogeneous requirements of NDE systems. The following section presents practical use cases in which AAS have been successfully employed in NDE applications.

5.1. Predictive Maintenance Application Using AAS

A representative example of AAS implementation is provided by the EMOTION research project [26]. To ensure the findability, accessibility, interoperability, and reusability (FAIR) of collected data, a robust data management platform is essential, particularly for enabling predictive maintenance and other data-driven approaches. In this context, Asset Administration Shell, functioning as the machine's digital twin, acts as a key enabler for advanced fault diagnosis and predictive maintenance in industrial settings [27]. The EMOTION project adopts the FAIR principles [28] and employs Piveau [29], an open-data platform with extensive experience in managing FAIR-compliant metadata datasets [30].

Piveau supports both automated API-based ingestion and manual data entry, generating metadata conforming to the DCAT Application Profile for data portals in Europe (DCAT-AP), including custom extensions where necessary. By adhering to standardized conventions, DCAT-AP enhances metadata quality and searchability across portals [31,32]. Within EMOTION, this ensures a consistent and efficient mechanism for querying and accessing information stored in the hosting database.

The predictive maintenance use case is illustrated using a digital representation of process monitoring for a 3D printer. This required the design and implementation of multiple AAS submodels, most of which were adopted from the IDTA [33] and the Interopera project [34]. Only the "Operation Submodel" had to be developed specifically for this application. The design process followed a structured methodology with the following steps:

- Requirements elicitation: Identification of relevant operational, monitoring, and maintenance information for the 3D printer together with domain experts.
- Analysis of existing submodels: Systematic review of AAS submodels published by IDTA and within the Interopera project to maximize reuse and ensure interoperability.
- Mapping and selection: Mapping the identified requirements to existing submodels (e.g., Digital Nameplate, Technical Data, Time Series, Predictive Maintenance) and selecting suitable candidates.
- Design of the Operation Submodel: Development of a new Operation Submodel to capture machine-specific executable functions (e.g., start/stop, parameter presets) not covered by existing submodels.
- Implementation and integration: Implementation of the selected and newly developed submodels in BaSyx and integration with the underlying data sources (MQTT, InfluxDB, predictive maintenance service).
- Initial verification: Consistency checks of the submodels and their data bindings using example workflows, such as starting the machine, monitoring sensor data, and recording anomalies.

This structured approach is transferable to other NDE systems by adapting the requirement analysis and mapping steps to the respective inspection technologies and use cases.

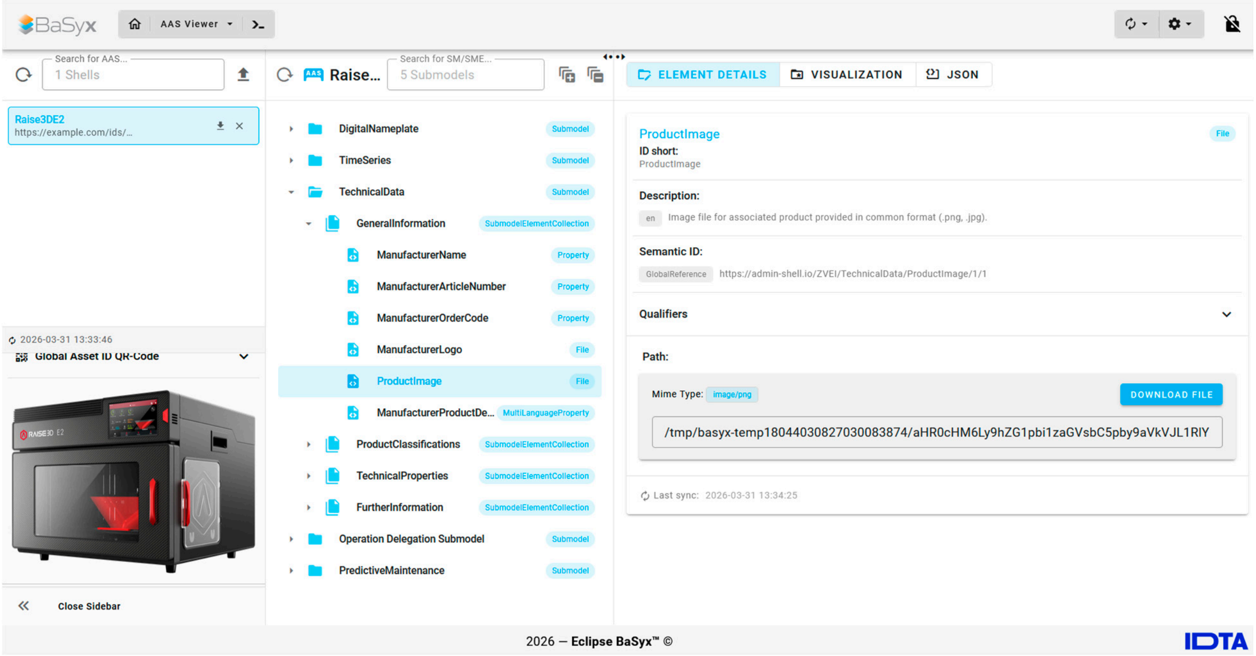
The principal submodels employed include:

- **Digital Nameplate Submodel:** Contains descriptive information on the manufacturer, suppliers, and other identification-related parameters of the 3D printer.
- **Technical Data Submodel:** Specifies the technical specifications of the 3D printer, including mechanical properties and the installed software version.

- **Operation Submodel:** Provides metadata describing the operational functions of the 3D printer, such as machine start/stop processes and other executable operations.
- **Time Series Submodel:** Defines metadata associated with the connected time-series database (InfluxDB), enabling structured access to process and monitoring data.
- **Predictive Maintenance Submodel:** Captures metadata relevant to predictive maintenance, supporting the analysis, planning, and execution of maintenance activities.

Beyond demonstrating the feasibility of an AAS-based representation for a 3D printer, this use case contributes a reusable pattern for integrating NDE-related process monitoring with FAIR-compliant data management and predictive maintenance services. It combines (i) systematic reuse and extension of standardized AAS submodels, (ii) integration with a semantic open-data platform (Piveau) based on DCAT-AP for metadata management, and (iii) a five-layer SOA that separates field-level data acquisition, time-series storage, digital twin representation, and service orchestration.

Figure 2 presents a section of the Asset Administration Shell and illustrates the underlying structural concept. As an example, the TechnicalData submodel is composed of additional submodels (GeneralInformation, ProductClassifications, TechnicalProperties, and FurtherInformation), which provide a more hierarchical structure of the machine-related properties.



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- DigitalNameplate Submodel
- TimeSeries Submodel
- TechnicalData Submodel
  - GeneralInformation SubmodelElementCollection
    - ManufacturerName Property
    - ManufacturerArticleNumber Property
    - ManufacturerOrderCode Property
    - ManufacturerLogo File
    - ProductImage File
    - ManufacturerProductDe... MultiLanguageProperty
  - ProductClassifications SubmodelElementCollection
  - TechnicalProperties SubmodelElementCollection
  - FurtherInformation SubmodelElementCollection
- Operation Delegation Submodel Submodel
- PredictiveMaintenance Submodel

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Figure 2. Image segment from the BaSyx UI (https://github.com/eclipse-basyx/basyx-aas-web-ui, Accessed at: 2 February 2026) of the Asset Administration Shell (AAS) of the 3D printer.

The digital representation of the 3D printer is embedded in a five-layer Service-Oriented Architecture (SOA), as depicted in Figure 3. The data pipeline originates at the Field Layer, which comprises the 3D printer and its sensors. These sensors transmit real-time quality data to the Communication Layer using MQTT. Within the Service Layer, components such as InfluxDB are employed for real-time data storage. A Predictive Maintenance Service operates on this layer, processing data from InfluxDB to identify anomalies and predict wear. Above these, the Digital Twin Layer hosts the AAS and its submodels, while the User Layer provides dashboards and process control interfaces. This architecture enables maintenance personnel to access up-to-date information on machine condition and to receive targeted maintenance instructions.

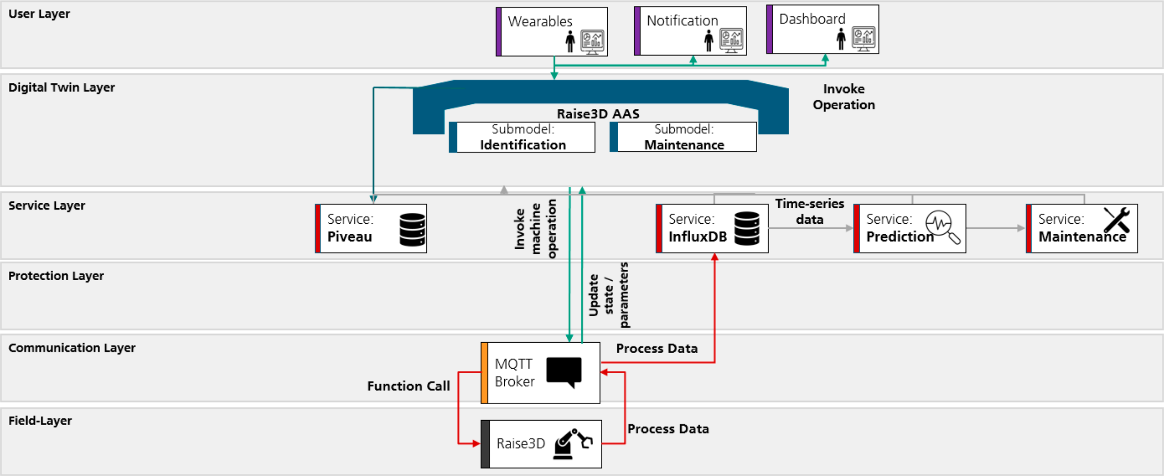


Figure 3. Representation of the 3D printer's data pipeline, including the classification within the administration shell.

When the user triggers the "Start Machine" function via the AAS interface, the 3D printer starts working. Throughout the process, sensor data are continuously forwarded to InfluxDB and documented within the Time Series Submodel of the AAS. In parallel, the Predictive Maintenance Service evaluates this data stream in real time. Upon detection of an anomaly, the system automatically shuts down the machine to prevent potential damage. Details regarding the detected anomaly are subsequently recorded in the Predictive Maintenance Submodel of the AAS.

This solution is part of an ongoing research project, so systematic validation is still required. Beyond the illustrative description provided here, future work will evaluate the approach using quantitative metrics such as prediction accuracy for fault and wear events, false-alarm rates, maintenance lead time, and resulting impacts on machine availability and overall equipment effectiveness. This evaluation will be based on controlled degradation experiments and long-term field data from the 3D printer and comparable equipment. The present paper therefore focuses on the architecture and digital representation concept, while detailed validation results will be reported in subsequent publications.

5.2. Integrating Asset Administration Shells as Foundational Knowledge Bases for Conversational Agents

The AAS can additionally function as a knowledge base for chatbots by providing structured access to NDE maintenance data. This enables key tasks such as fault diagnosis, retrieval of inspection records, and generation of predictive warnings. Using a natural language chat interface, maintenance personnel can interact with the system without requiring direct technical system access or conducting manual searches [35,36].

Related work has already demonstrated the combination of AAS with LLMs for quality control and industrial automation. Shi et al. [35] focus on interoperable information modeling for zero-defect manufacturing, and Xia et al. [36] explore LLM-based control of industrial automation systems. However, these approaches do not address NDE-specific knowledge bases, inspection workflows, or predictive maintenance scenarios. In contrast, our work targets the NDE domain and the 3MA micromagnetic inspection system, integrates AAS-based operational data (e.g., events, configuration, status) with a curated NDE knowledge base via RAG, and deploys an in-house, NDE-adapted LLM with explicit scaffolding. The resulting architecture is therefore tailored to NDE assistance tasks such as fault diagnosis, parameter selection, and interpretation of inspection results.

The proposed architecture consists of two key components: the AAS as the data source and a chatbot engine based on a Large Language Model (LLM) [35]. Maintenance-related information, such as event histories, detected anomalies, equipment conditions, and device characteristics, is stored within the AAS. The chatbot utilizes the LLM to interpret user queries and convert them into structured REST API requests [36]. Upon retrieving the relevant data from the AAS, the chatbot generates human-readable responses tailored to the specific device and context [37]. This approach removes the need for direct technical system access and manual data retrieval, thereby enhancing predictive maintenance workflows by accelerating diagnostic processes and reducing equipment downtime.

To achieve such a complex task, the unintended possible outcomes from AI models need to be minimized. The way to efficiently implement it is robust scaffolding of AI agents [38,39]. The scaffolding should be designed and then optimized specifically for each real-world use case. We have focused on building the AI agent scaffolding on the 3MA micromagnetic multiparameter inspection system, which detects near-surface microstructure, hardness, strength, and stresses in ferromagnetic materials for inline quality control [40]. We have systematically collected the institute's internal NDE knowledge from domain experts and integrated it into our data pipeline using a Retrieval-Augmented Generation (RAG) approach. This is necessary because open foundational models, which are typically trained on large-scale, publicly available datasets, often lack the depth of domain-specific expertise required for high-quality NDE reasoning and decision support. By combining expert knowledge, guidelines, reports, and historical case data with RAG, the system can retrieve and inject relevant NDE knowledge into the prompt context at inference time, thereby improving both the accuracy and relevance of the generated responses.

Building upon this, we have further advanced the approach by deploying an in-house Large Language Model (LLM) at the institute, which has been specifically fine-tuned on NDE-related domain-specific documentation. This tailored fine-tuning enables the model to better capture specialized terminology, inspection procedures, standards, and typical defect patterns encountered in NDE practice. As a result, the domain-adapted LLM provides reduced hallucination tendencies [41] and delivers more precise and context-aware outputs. In combination with the RAG [42] pipeline, this setup provides a robust foundation for NDE support applications, ensuring that responses are both technically sound and aligned with institutional best practices. Thus, combining all the technologies, we have developed a chatbot, as depicted in Figure 4 below.

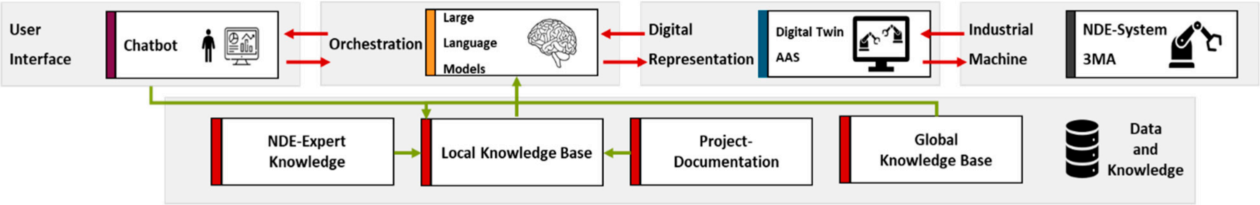
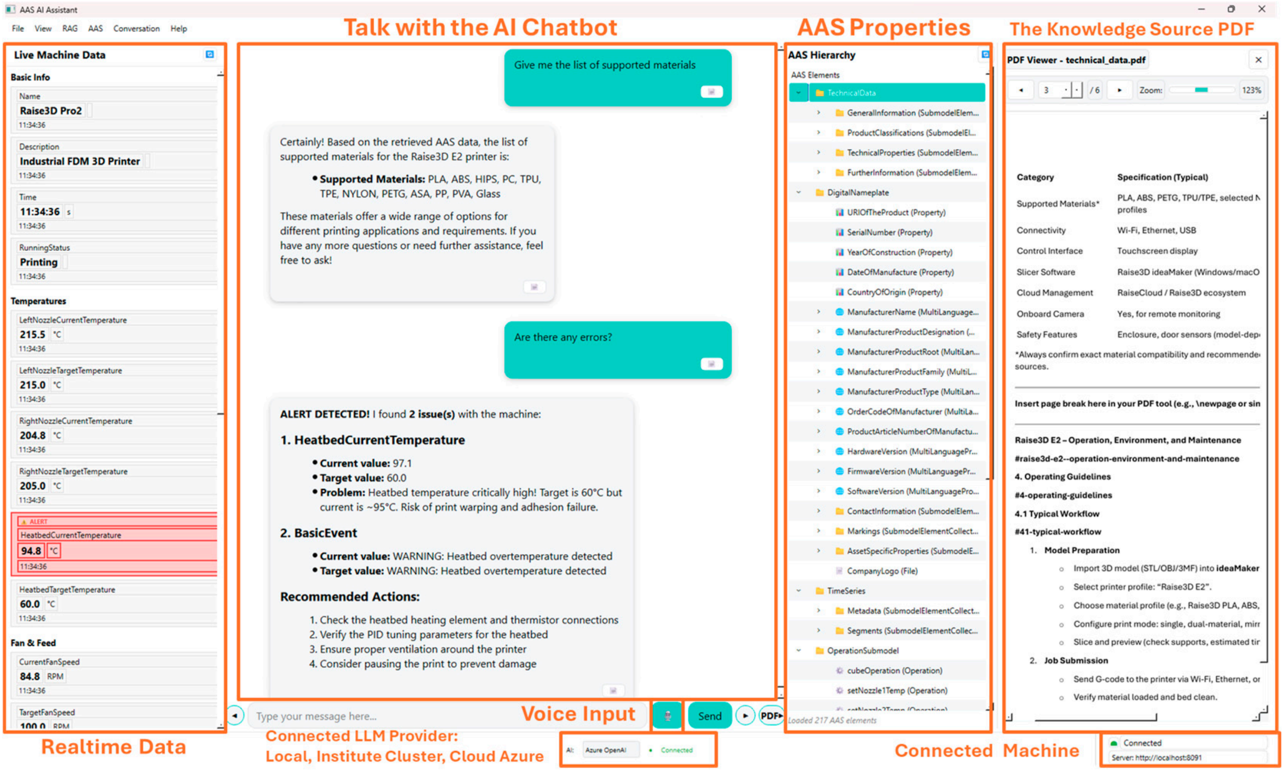


Figure 4. System Architecture of Integrated LLM, AAS and RAG for NDE Devices.

Figure 5 below depicts the front-end of the prototype chatbot application we have developed. The UI consists of four different segments that provide the user with information about the current use case. The chatbot itself is centrally located, enabling the user to interact with the LLM. Input is entered into the traditional way using a keyboard. Alternatively, an initial speech-to-text module has also been integrated. Voice output has not yet been implemented. In addition, the LLM used can be changed below. In the long term, both cloud-based and local LLMs are to be integrated here. To the right of the chatbot, the currently used administration shell and PDF sources are displayed, which serve as source references for queries. To the left of the chatbot, real-time data from the AAS can also be displayed, so that events, for example, are directly visible in the UI.



Live Machine Data

Basic Info

Name: **Raise3D Pro2** 11:34:36
Description: **Industrial FDM 3D Printer** 11:34:36
Time: **11:34:36** s 11:34:36
RunningStatus: **Printing** 11:34:36

Temperatures

LeftNozzleCurrentTemperature: **215.5** °C 11:34:36
LeftNozzleTargetTemperature: **215.0** °C 11:34:36
RightNozzleCurrentTemperature: **204.8** °C 11:34:36
RightNozzleTargetTemperature: **205.0** °C 11:34:36
⚠ ALERT HeatbedCurrentTemperature: **94.8** °C 11:34:36
HeatbedTargetTemperature: **60.0** °C 11:34:36

Fan & Feed

CurrentFanSpeed: **84.8** RPM 11:34:36
TargetFanSpeed: **100.0** RPM

Give me the list of supported materials

Certainly! Based on the retrieved AAS data, the list of supported materials for the Raise3D E2 printer is:

- **Supported Materials:** PLA, ABS, HIPS, PC, TPU, TPE, NYLON, PETG, ASA, PP, PVA, Glass

These materials offer a wide range of options for different printing applications and requirements. If you have any more questions or need further assistance, feel free to ask!

Are there any errors?

ALERT DETECTED! I found **2 issue(s)** with the machine:

1. HeatbedCurrentTemperature

- **Current value:** 97.1
- **Target value:** 60.0
- **Problem:** Heatbed temperature critically high! Target is 60°C but current is ~95°C. Risk of print warping and adhesion failure.

2. BasicEvent

- **Current value:** WARNING: Heatbed overtemperature detected
- **Target value:** WARNING: Heatbed overtemperature detected

Recommended Actions:

1. Check the heatbed heating element and thermistor connections
2. Verify the PID tuning parameters for the heatbed
3. Ensure proper ventilation around the printer
4. Consider pausing the print to prevent damage

Type your message here...

AI: Azure OpenAI • Connected

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Category	Specification (Typical)
Supported Materials*	PLA, ABS, PETG, TPU/TPE, selected N profiles
Connectivity	Wi-Fi, Ethernet, USB
Control Interface	Touchscreen display
Slicer Software	Raise3D ideaMaker (Windows/macO
Cloud Management	RaiseCloud / Raise3D ecosystem
Onboard Camera	Yes, for remote monitoring
Safety Features	Enclosure, door sensors (model-dep

*Always confirm exact material compatibility and recommende sources.

Insert page break here in your PDF tool (e.g., \newpage or sin

Raise3D E2 – Operation, Environment, and Maintenance
#raise3d-e2--operation-environment-and-maintenance
4. Operating Guidelines
#4-operating-guidelines
4.1 Typical Workflow
#41-typical-workflow

1. **Model Preparation**
   - Import 3D model (STL/OBJ/3MF) into **ideaMaker**
   - Select printer profile: "Raise3D E2".
   - Choose material profile (e.g., Raise3D PLA, ABS,
   - Configure print mode: single, dual-material, mirr
   - Slice and preview (check supports, estimated tir
2. **Job Submission**
   - Send G-code to the printer via Wi-Fi, Ethernet, or
   - Verify material loaded and bed clean.

Connected
Server: http://localhost:8091

Figure 5. First prototype of the chatbot UI for the interaction with AAS and RAG.

The current chatbot implementation is a prototype that demonstrates the feasibility of combining AAS-based digital representations with domain-adapted LLMs and RAG for NDE support. A systematic evaluation is ongoing and will assess answer correctness, citation accuracy, successful API invocations, robustness against ambiguous queries, and, most importantly, user-rated usefulness in realistic inspection and maintenance scenarios. As such, the present contribution should be interpreted as a conceptual and architectural demonstration, not as a fully validated production system. Additionally, the 3D SmartInspect project, an AR-guided ultrasonic NDE measurement system, is highly suitable for the application of a similar LLM-based architecture [10].

6. Conclusions, Limitations, and Future Work

This Perspective examined the role of digital representations and networking of NDE information and systems in the context of Industry 4.0. We argued that the increasing integration and interoperability requirements in industrial environments make it insufficient to exchange only control commands and simple status data. Instead, semantically rich, interoperable digital representations are needed to describe NDE systems, their operating states, and their inspection results in a machine-readable way.

OPC UA and the AAS offer essential foundations for digital representation. OPC UA enables the implementation of secure and standardized communication and information modeling. This includes the creation of so-called Companion Specifications for the domain-specific use of NDE. The AAS offers a flexible yet standardized approach for structuring asset information within submodels. With the help of lightweight protocols for transport, such as MQTT, the integration of NDE systems into a service-oriented architecture and IIoT is enabled.

In terms of specific implementations, we identified and described two exemplary prototypes. Firstly, we designed an AAS-based architecture for a 3D printer within the context of the EMOTION project, where we reused and extended existing standardized submodels (e.g., Digital Nameplate, Technical Data, Time Series, Predictive Maintenance, and a new Operation Submodel), and integrated them within a five-layered architecture for SOA, where the data acquisition is handled by an MQTT-based system, InfluxDB for the storage of the time-series data, and Piveau/DCAT-AP for the management of the FAIR-compliant metadata. Secondly, we designed a chatbot-based assistant system where we utilized an AAS-based structured data source for a 3MA micromagnetic inspection system and a domain-specific LLM and RAG pipeline to show the feasibility of a natural language interface for NDE knowledge and data.

These prototypes show the feasibility of the proposed solution at the architectural and integration level, as they verify that (i) NDE-relevant assets and processes can be mapped to standardized AAS submodels, (ii) the integration of MQTT, OPC UA, and AAS in a layer-based SOA for NDE-related monitoring and predictive maintenance is possible, and (iii) AAS-based digital representations can be used as a knowledge backbone for LLM-based assistance systems.

At the same time, the implementations are still in early stages and have not yet been quantitatively validated: for the predictive maintenance use case, so far, the focus of our research on the use case has been on the design of the concepts, the selection and extension of the submodels, and the end-to-end integration of the data pipeline, without quantitatively evaluating the accuracy of predictions, false-alarm rates, maintenance lead times, or availability and overall equipment effectiveness; for the chatbot-based assistant, the current prototype has been qualitatively evaluated in a lab environment, while extensive research on answer correctness, citation quality, robustness against ambiguous queries, and usefulness in real NDE scenarios is still ongoing, so the results in this paper should be considered conceptual and architectural in nature.

With respect to the predictive maintenance use case, quantitative evaluation of prediction accuracy, false-alarm rate, maintenance lead time, and machine availability still needs to be conducted, while for the chatbot assistant, user studies on answer correctness, citation quality, robustness to ambiguous queries, and usefulness for operators remain future work. In the meantime, further progress in the development of OPC UA Companion Specifications for NDE, reusable AAS submodels, governance, version management, security patterns, and alignment with EU Data Act [8] regulations will be important for the large-scale, multi-vendor deployment of digital representations in industrial NDE.

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