Realization of AI-enhanced Industrial Automation Systems using Intelligent Digital Twins

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Abstract

A requirement of future industrial automation systems is the application of intelligence in the context of their optimization, adaptation and reconfiguration. This paper begins with an introduction of the definition of (artificial) intelligence to derive a framework for artificial intelligence enhanced industrial automation systems: An artificial intelligence component is connected with the industrial automation system's control unit and other entities through a series of standardized interfaces for data and information exchange. This framework is then put into context of the intelligent Digital Twin architecture, highlight the latter as a possible implementation of such systems. Concluding, a prototypical implementation on the basis of a modular cyber-physical production system is described. The intelligent Digital Twin realized this way provides the four fundamental sub-processes of intelligence, namely observation, analysis, reasoning and action. A detailed description of all technologies used is given.

Keywords: Artificial Intelligence (AI), Cyber-physical production system (CPPS), Framework, Industrial Automation Systems, Intelligent Digital Twin Architecture, Prototype

1. Introduction

Mass customization [1] and high competition [2] require the industrial automation sector to greatly increase productivity as well as flexibility [3] or (re)configurability [4]. One approach to meet this challenge is the use of cyber-physical systems (CPS) equipped with artificial intelligence (AI). A CPS is "an integration of computation and physical processes through communication infrastructures" [5], which generally enables monitoring and controlling of the physical asset in an adaptive way [6]–[8].

The combination of the already existing networking and new AI capabilities of future industrial automation systems will then enable them to efficiently control real systems and to automatically adapt to new customer requirements without the need for knowledge or experience of system engineers and based only on environmental parameter analysis. One way to realize such combination was described by [9], which presented an architecture for the integration of AI within the Digital Twin, covering all necessary components of a Digital Twin to realize various use cases in an AI-enhanced industrial automation system.

Objectives: In this paper, artificial intelligence is first discussed generally and related to industrial automation forming a framework for artificial intelligence enhanced industrial automation systems (Sec. 2). Thereon, an architecture for an Intelligent Digital Twin is deduced, which enables the realization of this framework (Sec. 3). This architecture is then implemented based on various technologies prototypically, demonstrating its potential benefits in a modular cyber-physical production system (Sec. 4). Finally, a summary is given in Sec. 5.

2. Artificial intelligence in industrial automation

2.1 Definition of artificial intelligence

To properly comprehend and apply the term artificial intelligence in industrial automated systems, first the human intelligence process must be outlined.

Intelligence can be defined as the human ability to think abstractly and rationally and to thereby derive functional actions even in the face of new, meaning previously unencountered, problems [10]. From the authors' perspective, this human intelligence process can be described in four steps:

1. Observation and perception of information
2. Analyzation and (subconscious) storage of this information
3. Reasoning based upon analyzation results
4. Execution of reasoning results

The subsequent usage of previously analyzed or processed information to enhance reasoning in yet unencountered situations, commonly called ‘learning’, is a supplementary feature greatly enhancing performance without being required for basic intelligence.

Consequently, AI is an artificial system’s capability to act accordingly [11], [12], in our words: *AI is the technical transformation of aspects of intelligence – namely observing or perceiving, analyzing, reasoning and action – into a software with the goal of realizing a problem-solving automat*.

The field of AI consists of a large number of sub-fields, among which ‘modelling and simulation’, ‘pattern recognition’, ‘knowledge-based systems’, ‘robotics’ and ‘machine learning’ represent the most prominent examples. Due to the strong similarities between AI systems’ features in all of these sub-fields, the definition of a general AI framework for industrial automation systems (IAS) is feasible.

2.2 AI framework for industrial automation systems

The authors’ framework for an AI-enhanced IAS is depicted in Fig. 1. It is based on the idea of an *AI Component* enriching conventional *IAS* via new interfaces.

This *AI Component* is software situated in the cyber-part of a CPS, either locally or in a cloud service accessed via a global area network. It collects data supplied by the *IAS* via a *Data Acquisition API* and its own *Information API*. Its *Networking API* might provide additional information, giving access to other entities, e.g. machines, environment representations or users, via common network interfaces. Inside the *AI Component*, the intelligence process is then carried out using the information available. The results thereof are relayed to the *IAS* via the *Feedback API* in order to be executed. The *Feedback API* is used, for example, to transfer new control code generated in the *AI Component* to the system’s *Control Unit*.

Finally, the *AI2AI API* provides a direct communication interface between different *AI Components*, either in-domain or cross-domain. This allows for the sharing of knowledge and increases the overall performance of such systems.

In order to realize such AI-enhanced IAS, the Intelligent Digital Twin can be utilized, providing an already existing framework of concepts and interfaces for the implementation of AI functionalities.

3. Intelligent Digital Twin

Generally, a Digital Twin (DT) is a “virtual representation of a physical asset in a CPS, capable of mirroring its static and dynamic characteristics [13]. It contains and maps various models of a physical asset, of which some are executable, called simulation models. Within this context, an asset can be an entity that already exists in the real world or can be a representation of a future entity that will be constructed.” [9]

An Intelligent Digital Twin (IDT) is an extension of this definition, encompassing the features enumerated above enhanced by the ability to observe its physical environment and to analyze and learn from it, so that existing models can be adapted or the real asset’s interaction with the environment caused. The architecture presented in [9] and depicted in Fig. 2 is therefore to be understood as a specific manifestation of the framework for AI-enhanced IAS described in Sec. 2.2:

As within the conventional DT, the IDT is based on the *Models* of the real asset it represents. Furthermore, it incorporates a *Model-Management* to access the different versions thereof, which were created in previous phases of its lifecycle [14]. In order to continuously stay synchronized with those potentially changing [15] interdisciplinary models, a *Synchronization Interface* is provided. A *DT-2-DT Relations*

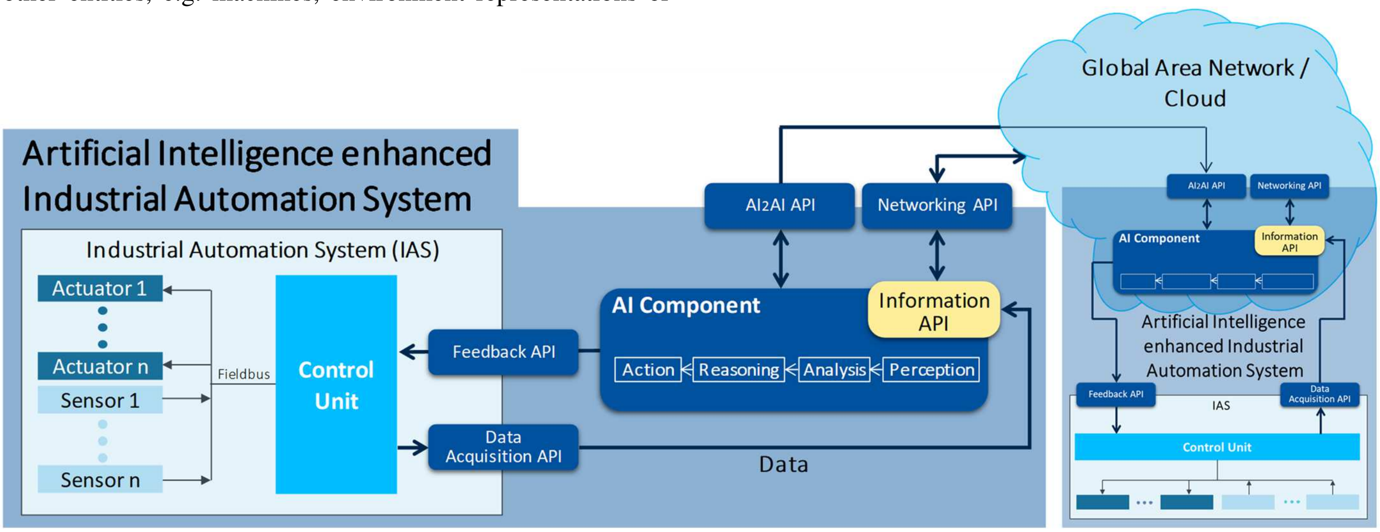

Fig. 1. AI-enhanced industrial automation system and its components and interfaces

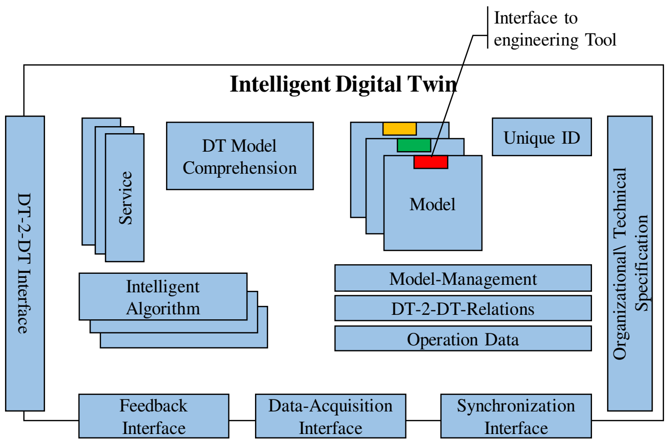

Fig. 2. Architecture of the Intelligent Digital Twin according to [9]

component then adds information about other DTs and their relation to itself.

Still exactly like in a conventional DT, an IDT contains a *Unique ID*, allowing identification and addressing of the DT throughout its lifecycle, an *Organizational or Technical Specification* component, containing meta-data on the real asset, as well as a *Data Acquisition Interface* collecting and storing *Operation Data* from the real asset.

However, an IDT consists of several additional components, going beyond the functionality of a conventional DT: A *DT Model Comprehension* component adds the capability to understand and manage all models and data based upon semantic descriptions. Furthermore, all the *Services* the real asset can provide, are stored. And, finally, all information provided by the components mentioned so far can be used by *Intelligent Algorithms* providing AI functionalities, e.g. as listed in Sec. 2.1. The results thereof are then transferred back to the real asset via semantic technologies through the *Feedback Interface*. An interface for communication with other IDT, the *DT-2-DT-Interface* completes the framework, allowing semantic exchange of data, models or relations. This interface combines both, the AI2AI API and the Networking API of the AI-enhanced IAS framework.

4. Implementation of an intelligent Digital Twin

To realize the presented architecture, a modular production system (MPS) and its IDT were implemented. The MPS is an automated system in discrete manufacturing consisting of twelve main functional groups (modules, short: FG) that together manufacture a product. These FGs are all controlled by a central PLC. At the same time, their respective decentralized control systems contain Raspberry Pi's, which enables decentralized control.

In this system, a plastic work piece (as a product) is processed in various stations of the system. Fig. 3. illustrates the MPS and its FG, namely Stack Magazine, Height measurement, Turn, Drill, Drilling hole test, Insert, Press and Sorting out FGs. In addition to these FGs, the system consists of four conveyor belt FGs, each containing a motor, a belt and several light sensors that collectively transport the work piece to the workstations. The complete system includes 32 sensors and 90 actuators.

The manufacturing process begins in the MPS with the transfer of the work piece through a stacking magazine on the conveyor belt. The *Stacking magazine FG* has the task of storing the work pieces and pushing them out to the transfer belt. Once the work piece is on the conveyor belt, it is detected by the sensors and the conveyor belt transports it to the *Height measurement FG*. In this FG, the sensors are used to check whether the work piece has the correct height. In the next processing stations, the work piece is first lifted and then turned by the grippers of the *Turning FG*, then a hole is drilled by the *Drilling FG* on the upper side of the work piece. After drilling the hole, the work piece is checked in the next station by the *Drilling hole test FG*. When the work piece has reached the correct position and the light sensors of the FG are triggered, its test pin moves downwards. If the work piece has been drilled correctly, the test pin can reach the lower end position. In the next station, a nut is inserted into the drilled hole using the *Insert FG*. The *Press FG* is responsible for pressing the nut into the hole if it has not completely been inserted into the hole yet. The last step is carried out by the *Sort out FG*: Its function is to sort out the work piece via its sensors if necessary. If a drilled work piece without a nut is detected, the work piece is considered defective unless this specific work piece was ordered without a nut.

In order to realize the architecture described in Sec. 3, an IDT of the MPS is implemented. It consists of various models and their relations, operation data and an interface for active data acquisition, organizational and technical specifications, synchronization interface, feedback interface, model of possible services that different actuators can perform, AI-algorithms and, finally, a model comprehension component.

Fig. 3. Modular Production System and its Functional Groups (FG)

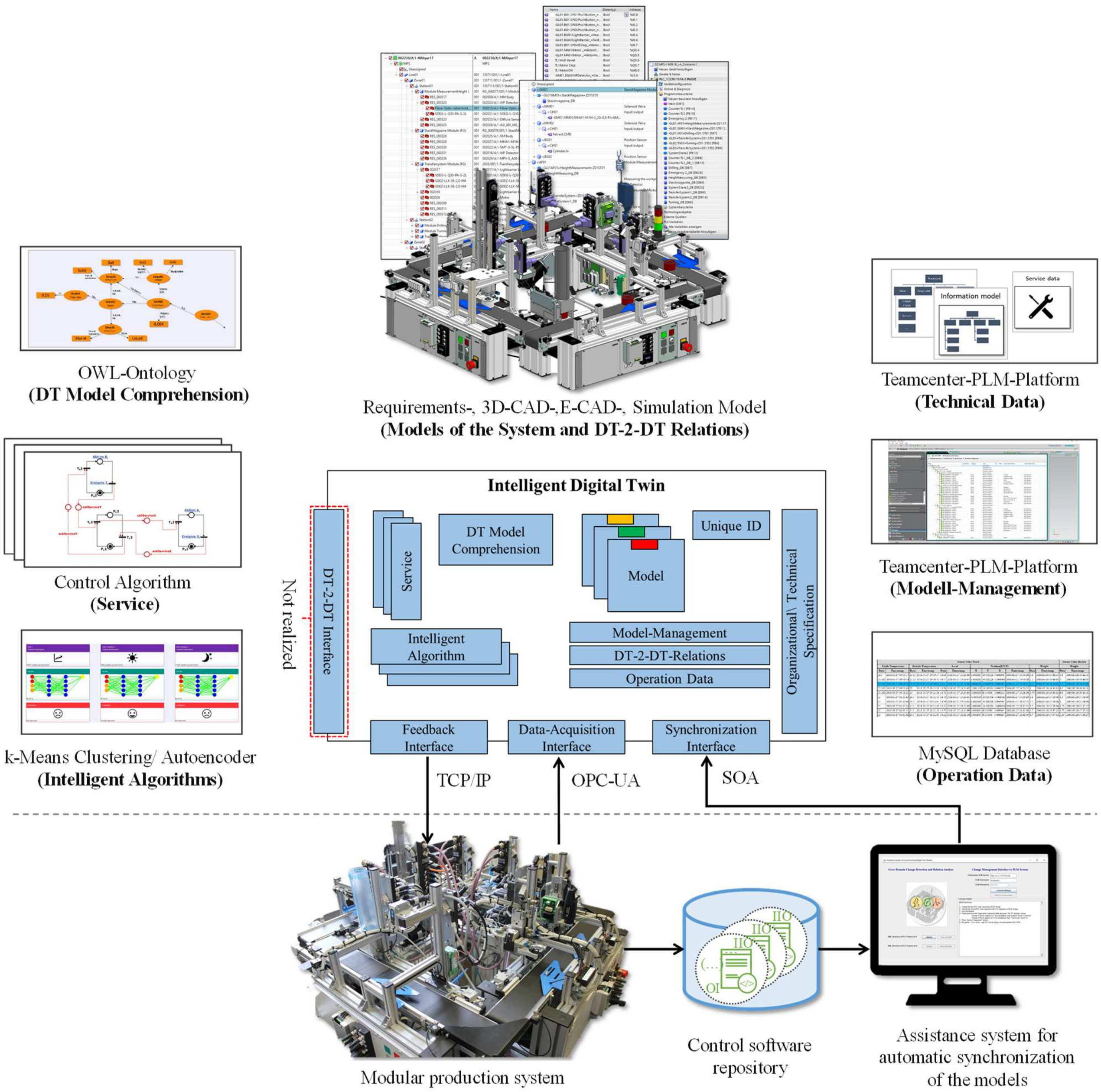

Fig. 4. Intelligent Digital Twin of the Modular Production System

Fig. 4. summarizes the implemented technologies and components of the IDT.

The IDT of the MPS consists of all its multi-disciplinary models, e.g. its 3D CAD, electrical circuit, functional and simulation models, as well as the organizational and technical specifications in the Teamcenter PLM-Platform under a unique ID for each mechatronic component in the system. Within this demonstrator, the tools NX-Modeling, Line Designer, Automation Designer, TIA-Portal, and PLCSIM Advanced were used to create multi-disciplinary models of the DT of the MPS on the Teamcenter PLM-Platform. In this case, the SOA interface of the PLM-Platform is used as the DT's model synchronization interface. This interface allows access to the engineering models of the MPS for system engineers or for assistance systems to synchronize them automatically: In [9] and [15] the authors have described in detail a concept for the automated synchronization of the models of the DT and its realization by means of an assistance system.

This assistance system detects the changes in the system by means of rule-based analysis of the system's control software at different time points and automatically adapts them to the models of the DT by means of its SOA based interface.

The Raspberry Pi's, Ethernet, TCP/IP and a database are used to implement the active data acquisition and operating data components (dynamic and historical sensor data) in the architecture.

The AI algorithms used for this work are k-means clustering and autoencoder, by which the information model (model comprehension component in the architecture) can be extended automatically by analyzing the operating data in the database. These algorithms dynamically analyze all sensor and actuator data to discover the relations between them and generate an information model from all components of the system. For the realization of the information model, the ontology method was used. In the architecture, the information model is realized with OWL technologies. It consists of various abstract models, sub-models and their dependencies in semantic technology.

Additionally, a feedback interface with TCP/IP, Raspberry Pi's and Ethernet is implemented between the IDT and the MPS. This interface is used to transmit IDT commands to Raspberry Pi's as a service. This allows the actuators in the system to be controlled by the IDT.

The implementation of the DT-2-DT interface was not the focus of this work. However, the authors work on various technologies such as OWL, agent and cloud technologies in the context of standardizing data exchange in a semantic network for the implementation of a DT-2-DT interface. This will be reported on in the authors' next publications.

5. Conclusion

This paper gives a vision about the future of industrial automation systems, which are equipped with artificial intelligence algorithms. Accordingly, in this paper a framework for intelligent industrial automation systems was presented, which can fulfill the four characters of an intelligent system: "Observation and perception of information", "Analyzation and (subconscious) storage of this information", "Reasoning based upon analyzation results" and "Execution of reasoning results". Consequently, an architecture for an Intelligent Digital Twin was presented, which can realize the characters of the AI component within this framework.

Furthermore, this framework of the AI-enhanced industrial automation system was realized by implementing a real asset (a modular production system) and it's Intelligent Digital Twin with various technologies. Lastly, the applied technologies and interfaces between the real asset and intelligent Digital Twin have been described.

The implemented intelligent modular production system using the Intelligent Digital Twin enables the system to react automatically to new customer requirements regarding new products through the automatic generation of new control code for the system based only on environmental parameter analysis. In other words, the Intelligent Digital Twin is able to control and (re-)configure the real system fully automatically.

The authors are currently working on the concept of semantic networking of Digital Twins using cloud technology to realize a DT-2-DT interface within the architecture of an Intelligent Digital Twin to be presented in future publications.

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