How Data Models Can Contribute to Linking Real-Life Assets with their Digital Twin – A Case Study in Predictive Maintenance

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Abstract

The basic concept of a digital twin as widely used mandates the existence of an original counterpart – most commonly dubbed as "real" – which is represented by the digital instance. Subsequently, this co-existence of the real and digital twins poses a continuous interoperability issue between the physical and digital world. While in theory, the mapping of e.g. physical to digital properties is trivial, in practice, it usually is not. This paper presents a case study on how this interoperability problem can be addressed by the use of a unified data model for predictive maintenance applications, which has been developed in the EU-funded innovation action UPTIME.

Keywords

Paper template, paper formatting, CEUR-WS

1. Problem Statement

Digital Twins are commonly understood as "digital replications of living as well as non-living entities" [1] and sometimes also as means to represent intangible entities like processes [2]. While the definitions are as diverse as the domains to which digital twin concepts are applied to nowadays [3], all concepts rely on the interaction between the real and digital counterparts. While technology has made rapid progress over the last decade on the availability and integration of sensors and asset connectivity, the developments have also created a plethora of closed or semi-closed frameworks through which the digital twins are fed. This near-inevitable vendor lock provides a great hurdle in the extensive adoptability of the digital twin technology as it discourages the integration of complementary systems side by side. Furthermore, the prevailing systems are often built towards a specific digital twin application (e.g. simulation or visualisation) which hinders cashing in scale effects and the transfer of applications between domains.

2. Digital Twins and Data Models

While in public perception, digital twins are most commonly associated with the applications which are realised based on them (e.g. 3D visualisations), the main component of a digital twin is really the data it holds and subsequently the architecture and structure it utilises to do so. [3], [4] The different angles, from which digital twins are designed and implemented, naturally introduce different architectures. However, the vast majority are built around a more or less simple structure which identifies the represented asset and corresponds with the respective counterparts of the real twins structure.

The asset breakdown structure can be detailed to very different depths, depending on the needs of the application. The properties and meta data which the digital twin holds about its real counterpart are then usually mapped onto this core structure. Many implementations of Digital Twins have a concise

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physical object in their focus [5], which defines the asset breakdown structure used for the digital twin. While this provides clear connections between the digital and physical twins, their components and states, modelling and including external systems is increasingly difficult. Thus some architectures foresee the possibility of linking different digital twins and jointing their algorithms, e.g. for co-simulation [6].

Like the focus of implementation, also the approach to data storage and modelling varies significantly. For applications, in which the data to be managed is known precisely and / or which are tailor made for a specific application, a rigid data model can be applied for maximum efficiency and ease of use [7]. In cases, where interaction between digital twins is necessary or where integration of external systems is needed, however a simple tailor-made data model usually does not provide enough flexibility in itself. Here the usage of standardised modelling languages has been established [8]. This also ensures some extensibility for future integrations.

With an increase in complexity of the asset and data structure at the same time also the complexity of the connection of the two twins grows as an increasing complexity is often followed by increased data volumes. For especially complex assets or when the digital twin is not only concerned with a single component but a whole assembly or fleet of products this growing complexity can easily lead towards a categorisation as big data application. In these cases, the architecture cannot sensibly be assessed for the isolated digital twin but only as a co-existence of both physical and digital twins. With moving the physical and digital twins closer together the paradigm of edge vs. cloud processing becomes one of the core issues [9]. The gap between physical and digital twins does not exclusively generate its importance from the complexity of the twins and their constraints but is also from the aspired versatility of the system and its applicability to diverse applications scenarios.

3. Bridging the Gap between Real-life and Digital Twins

While the different shapes, that the current implementations of digital twins are in, are arguably fit for purpose to address the respective application and sector, a challenge for progressing the current state of the art is creating a universally applicable structure for digital twins / representations, which is not limited to the peculiarities of few application / sector combinations.

The "UPTIME – Unified Predictive Maintenance" project is creating a predictive maintenance system aimed at manufacturing and logistics applications utilising the digital twin paradigm. Due to the objectives of the action the system needs to be applicable to an extremely wide range of application scenarios. At the same time this puts the gap between physical and digital twins into the spotlight, as the universal applicability raises the aforementioned issues. In the system definition process the question of a unified data model which is applicable to a diverse set of digital twins has been identified as one of the main topics.

The UPTIME project has initiated the work on an unified data model with a focus on the scope of information managed in a Predictive Maintenance solution, and how they are related. The resulting business data model allows both final users and technical partners to understand the logic behind the solution and associated processes, and how the different required inputs work together to provide the expected service. The UPTIME Business Data Model is not a technical data model, but rather the logical view which provides a framework for that technical data model and a visual & simplified way to explain it. For it six main areas have been identified with their main interactions. Figure 1 gives an overview of these data themes.

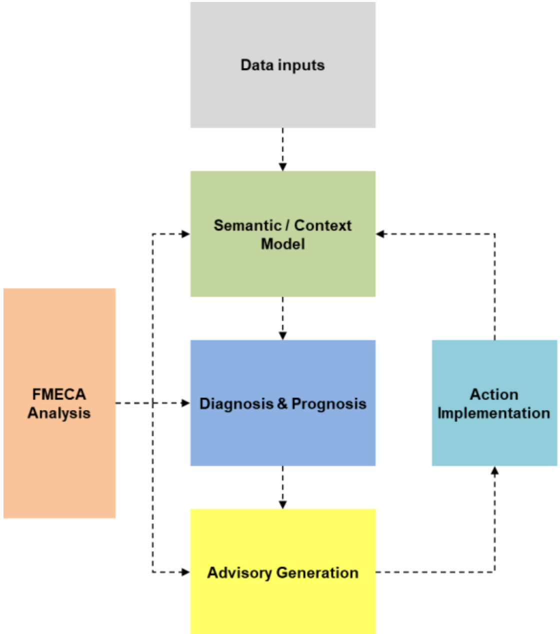

Figure 1: High level UPTIME Business Data Model

The arrows in the figure represent the key relationships between the distinct groups of data and is the link to the functional model of the project. The Semantic/Context Model information serves as the transverse structure for all other information. At the same time, the FMECA analysis serves as the knowledge base for UPTIME, and drives the key functionalities of Diagnosis, Prognosis, and Advisory Generation. Finally, the follow-up of Action Implementations can be used to update the models for more relevant results. The following table iterates the individual data themes which are used in the model.

Table 1: UPTIME Business Data Model Data Themes

Data Theme	Description
Semantic / Context Model	Model logically describing the system that is to be monitored through predictive maintenance, down to the different sensors and maintainable items and their relationships
FMECA Analysis	Model describing in detail the different failure modes of the system
Data Inputs	Inputs collected from the monitored system and relevant information systems, to be used in the Diagnosis and Prognosis algorithms
Diagnosis & Prognosis	Information used to define the Diagnosis & Prognosis algorithms in accordance to the monitored failure modes
Advisory Generation	Information used to define the decision algorithms for the advisory generation
Action implementation	Information managed in the context of the implementation of a maintenance action (if managed within the solution)

Based on this high level busines data model the individual processes have been mapped into a detailed data model listing and linking the data classes. While this can partially be translated into a technical data model, it is an important step in order to be able to link the different data classes to business processes and merits. Figure 2 gives an overview of the detailed business data model.

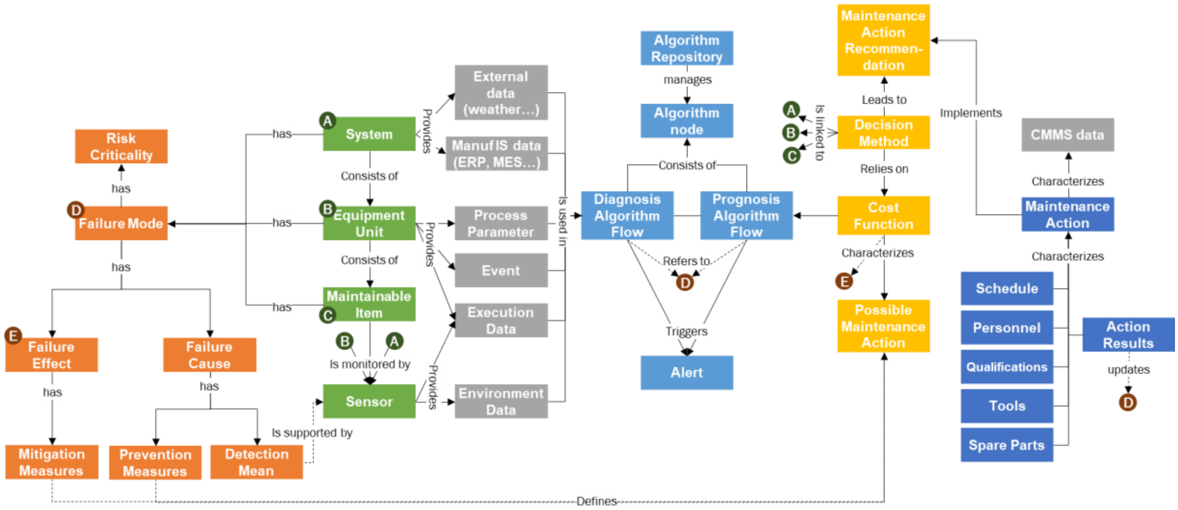

Figure 2: Detailed UPTIME Business Data Model

4. Conclusion

This paper has given an insight into a business-oriented approach to modelling the relevant data of a predictive maintenance system. In the UPTIME project, this has been deployed to create a unified technical data model for a wide variety of use cases while retaining a high level of flexibility and component integration. Together with the modelling of the business processes and customer journeys this business data model has helped significantly to join the business and technical perspectives of the project.

While not in the scope of the UPTIME project future research should be directed at transferring this approach towards dynamic data environments and models. On the technical level representing such constructs in ontologies or as graph collections is established, but the business data modelling perspective is often lacking.

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References

[1] A. El Saddik, „Digital Twins: The Convergence of Multimedia Technologies", *IEEE Multimed.*, Bd. 25, Nr. 2, S. 87–92, Apr. 2018, doi: 10.1109/MMUL.2018.023121167.

[2] E. ANDALUZ, „The Process Digital Twin: A step toward operational excellence", *Microsoft Industry Blogs*, Okt. 23, 2017. https://cloudblogs.microsoft.com/industry-blog/manufacturing/2017/10/23/the-process-digital-twin-a-step-toward-operational-excellence/ (zugegriffen Feb. 13, 2020).

[3] W. Kritzinger, M. Karner, G. Traar, J. Henjes, und W. Sihn, „Digital Twin in manufacturing: A categorical literature review and classification", *IFAC-Pap.*, Bd. 51, Nr. 11, S. 1016–1022, Jan. 2018, doi: 10.1016/j.ifacol.2018.08.474.

[4] M. Grieves und J. Vickers, „Digital twin: Mitigating unpredictable, undesirable emergent behavior in complex systems", in *Transdisciplinary perspectives on complex systems*, Springer, 2017, S. 85–113.

[5] A. Redelinghuys, A. Basson, und K. Kruger, „A six-layer digital twin architecture for a manufacturing cell“, in *International Workshop on Service Orientation in Holonic and Multi-Agent Manufacturing*, 2018, S. 412–423.

[6] B. A. Talkhestani *u. a.*, „An architecture of an intelligent digital twin in a cyber-physical production system“, *-Autom.*, Bd. 67, Nr. 9, S. 762–782, 2019.

[7] N. Kousi, C. Gkournelos, S. Aivaliotis, C. Giannoulis, G. Michalos, und S. Makris, „Digital twin for adaptation of robots’ behavior in flexible robotic assembly lines“, *Procedia Manuf.*, Bd. 28, S. 121–126, 2019.

[8] G. N. Schroeder, C. Steinmetz, C. E. Pereira, und D. B. Espindola, „Digital Twin Data Modeling with AutomationML and a Communication Methodology for Data Exchange“, *IFAC-Pap.*, Bd. 49, Nr. 30, S. 12–17, Jan. 2016, doi: 10.1016/j.ifacol.2016.11.115.

[9] K. M. Alam und A. El Saddik, „C2PS: A digital twin architecture reference model for the cloud-based cyber-physical systems“, *IEEE Access*, Bd. 5, S. 2050–2062, 2017.