PhD Position (*3 years*)

Contribution to Cognitive Digital Twin for Prognostics and Health Management of Production Systems: enabling cognitive capabilities through Machine Learning and Ontologies

Keywords: cognitive digital twin; ontology; artificial intelligence; prognostics and health management; productions systems.

Organisation:

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Description:

The emergent technology of Digital Twin (DT) is employed for several objectives in the manufacturing context and, among them, for predictive maintenance and Prognostic and Health Management (PM&PHM). The ad hoc DTs proposed in the literature are generally focused on one component of the manufacturing systems and on one/few services of the PM&PHM pipeline (ISO 13374–2:2007), like state detection, or diagnosis, or health assessment, or prognostics, or maintenance optimisation. For example, Tao et al. (2018) presented a DT driven PM&PHM method for improving the accuracy of prognosis and applied it to a gearbox case study; Aivaliotis et al. (2019) proposed a methodology to calculate the RUL of a machinery equipment by using DT and physics-based simulation models; Wang et al. (2019) presents a DT reference model for rotating machinery fault diagnosis; Liu et al. (2024) proposes a DT-based anomaly detection framework for real-time tool-condition monitoring in machining; Zappa et al. (2024) presented an ontology-based DT aiming at supporting the maintenance fault diagnosis decision-making process in manufacturing systems and applied it on a bearing of a laboratory platform.

Recent review papers (van Dinter et al., 2022; Xiao et al., 2024) have provided deep states-of-the-art in the field of DT for PM&PHM of production systems showing that nowadays the topic is quite explored in the literature and highlighting the interest of the scientific community on this research subject, as well as challenges and gaps. For example, one gap that emerged from van Dinter et al. (2022) is that most of the studies discussed the use of DTs on a component level, for instance, bearings or gearboxes, whereas system-level DTs aimed to perform predictive maintenance on a complete system (like production line or complex machine) are less common. Only one study, i.e. Xu et al., 2019, discusses the use of System-of-Systems DT for predictive maintenance of a whole shop floor. Similar results were found also in Xiao et al. (2024), who reported that current literature is mainly applied for fault detection of a single component of an equipment or machine.

Therefore, a challenge is in the integration of several DTs providing different PM&PHM services for several components; it has been identified as a promising direction to enable system level PM&PHM.

Toward this aim of connected DTs, recently the new concept of "Cognitive Digital Twin" (CDT) has emerged in the literature and proposed as an extended version of DT aiming to semantically interlink digital models enabling their seamless cooperation. The term CDT firstly appeared in the industry sector by Adl (2016) and was defined as "*a digital representation, augmentation and intelligent companion of its physical twin as a whole, including its subsystems across all of its life cycles and evolution phases*". Currently, the CDT starts to be more explored in the scientific literature and shows a promising evolution of the DT concept towards a more intelligent, comprehensive, and full lifecycle representation of complex systems (Rožanec et al., 2022; Zheng et al. 2022). Particularly, the CDT can be envisioned as an extended version of DT (therefore, including the 3 main elements of a DT: (1) a physical entity, (2) a digital entity, and (3) the bidirectional connections between the virtual and physical entities) containing multiple DT models with unified semantics (Zheng et al., 2022). Also, a CDT leverage some human-like cognitive capabilities, such as attention, perception, memory, reasoning, learning, and problem-solving, in order to enable decision making in complex and uncertain environment. These features allow the CDT to continuously evolve with the real system throughout its lifecycle, adapting to dynamic changes and unpredictable disruptions (ElMaraghy & ElMaraghy 2022). Although it seems that we're still a long way from achieving this objective in full, the fast development of digital technologies in a broad sense (including artificial intelligence, semantic technologies, machine learning, IIoT and ubiquitous sensing technologies) will enable achieve cognition capabilities at a certain level (Zheng et al., 2022).

Thus, a revised CDT definition has been recently provided by Zheng et al. (2022): "*Cognitive Digital Twin (CDT) is a **digital representation** of a **physical system** that is augmented with certain **cognitive capabilities** and support to execute **autonomous activities**; comprises a set of **semantically interlinked digital models** related to different lifecycle phases of the physical system including **its subsystems and components**; and **evolves continuously** with the* *physical system across the entire lifecycle*".

As evident from the definition, cognitive capabilities are essentials features that distinguish CDT from DT and enable a higher level of autonomy and intelligence, for example dealing with uncertain and evolving environment and generating dynamic strategies in an autonomous way.

To enable these cognitive capabilities, some key technologies are essential. For example, perception and attention can be triggered using IoT and data-driven algorithms (Kaji et al., 2020; Zenisek et al., 2019). Memory can be obtained using persistent technologies like databases (including new types like NoSQL and timeseries databases) or domain knowledge technologies, like ontologies (Eirinakis et al., 2022). Reasoning capability can be enabled by employing AI algorithms (Barthelmey et al., 2019) as well as ontologies (Wang et al., 2021), whereas learning can be activated by machine learning algorithms (Khan et al., 2020).

Some CDT architectures, their main elements and the key technologies enabling the CDT have been proposed in the literature. However **a CDT conceptual and/or operational framework for the PM&PHM of production systems was not found**. Moreover, as reported in the gaps/challenges of D'Amico et al. (2024), the **enabling technologies for enhancing cognitive capabilities of DTs, such as ontologies, knowledge graphs, AI, machine learning techniques, are not sufficiently explored**. According to this and the description provided above, the **objective** of the PhD is two-fold: **(1)** defining a CDT architecture and its main elements for enabling PM&PHM of production systems; **(2)** modelling and semantically integrating several DTs for enabling the collaboration of different components and/or PM&PHM services, and then supporting the PM&PHM of production systems.

This objective logically leads to 2 main research questions (**RQ1 and RQ2**). The first research question arising is:

- ***RQ1***. *What are the elements that must constitute a CDT functional architecture for enabling the PM&PHM of production systems?*
    - ***RQ1.1*** *What are the technologies/methodologies habilitating the cognitive capabilities of a CDT for PM&PHM?*

Considering that PM&PHM encompasses several steps (from Data Acquisition to Advisory Generation (Abbate et al., 2024)), a CDT framework should report the main "constituting elements" enabling the interaction among the PM&PHM steps of several components of a production system leveraging the cognitive capabilities. For example, AI technologies and ontologies, both recognised as enablers of PM&PHM process and cognitive capabilities in DT, should be considered as one of the main elements, probably coupled with the human in the loop in order to fully achieve the cognition in CDT for PM&PHM.

Indeed, as reported in many reviews (see for instance Biggio & Kastanis, 2020; Fink et al., 2020; Nguyen et al., 2023), all PM&PHM steps will benefit from leveraging data-driven AI algorithms. At the same time, the adoption of ontologies for PM&PHM enables knowledge representation, expressiveness and reasoning capabilities, inference potentialities and interoperability among PM&PHM steps (Abadi et al., 2022; Franciosi et al., 2022; Karabulut et al., 2023). As a logical conclusion, the integration of both should lead to the emergence of a CDT enabling the seamless integration of PM&PHM steps for manufacturing systems.

Furthermore, several advantages can be achieved through the coupling of data-driven methods (1) and knowledge-based methods (2) because they are complementary: the first (1) show advantages in terms of accessibility and accuracy, while the reliability could be poor; however, the second (2) have insufficient performance but good interpretability and context awareness (Li et al., 2022). As reported in Franciosi et al., (2024), a future research direction could be to explore the combination of machine learning, ontologies, and reasoning for the predictive maintenance of complex systems through the development of combined knowledge-based and data-driven approaches. On the one hand, machine learning algorithms can enable the extraction of concepts and patterns (as machine degradation models) from data or the calculation of information (as specific indices) that can then be enriched due to the querying performed by maintenance domain ontologies and rule-based reasoning on this input data. On the other hand, data from various sources and systems within a facility could be integrated to gather accurate information in order to create accurate models.

The second research question arising is:

- ***RQ2.*** *How to model and semantically integrate several DTs for enabling PM&PHM of production systems?*
    - ***RQ2.1.*** *How to model the knowledge and organize data and information in order to enable the collaboration among several DTs related to different components and/or PM&PHM services, and then supporting the PM&PHM of production systems?*

Considered the above RQs, it is expected the exploration of the combination of ontologies and data-driven AI (such as deep learning) in each step or combination of steps of the PM&PHM framework for integrated predictive maintenance decisions on one specific component (one DT) and/or with other components of the considered system (several DTs). Therefore, the response to the RQ2 (and RQ2.1) will allow the implementation of the CDT architecture defined in response to the RQ1 (and RQ1.1).

As reported in Franciosi et al. (2024), a possible future direction could relate to the development of a PM&PHM-integrated system through the employment of ontologies that could serve as the backbone for the integration of the PM&PHM steps. As such, the ontologies would work with other approaches and algorithms developed at different PM&PHM steps, and due to ontology's capability to provide context awareness and perform reasoning, it will deduce the proper information for the algorithms along the PM&PHM pipeline. Also, when heterogeneous databases of production systems' units are available, the ontology can provide a common semantic level, allowing for queries on heterogeneous databases (Medina-Oliva et al., 2014).

Moreover, as recently reported by D'Amico et al. (2024), even if ontologies and knowledge graphs are promising solutions for the semantic integration of heterogeneous DT models, further research is needed to explore their full potential.

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