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Hybrid knowledge based system supporting Digital Twins in the Industry 5.0

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Abstract

Digital twins are employed to monitor, analyze, and predict the behavior of a manufacturing system. In literature, the concept of digital twin is mainly associated with simulation models, and only a few works addressed the integration between physics-based and data driven models. This work extends this definition and describes how different kinds of knowledge can be integrated in a hybrid knowledge based system supporting digital twin. Following the Industry 5.0 paradigm, the hybrid system can improve the human-centricity, sustainability, and resilience of a manufacturing system. The hybrid digital twin is structured as an enterprise information system, which can be connected to the other information systems of the company, such as ERP, MES, and PLM, as well as other platforms of total quality management and total productive maintenance. A discussion on the application of the proposed approach in fusion welding, as an example of a very complex process, is also presented.

Keywords: Digital Twin; Hybrid Model; Knowledge Based System (KBS); Industry 5.0.

1. Introduction

In our society, the knowledge is the source of the highest quality power: markets, products, technologies, competitors, regulations and even societies change rapidly, and, for such reason, continuous improvement and the knowledge enabling such improvement and innovation has become important sources of sustainable competitive

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advantage. Hence, firms today consider knowledge and the capability to create and utilize knowledge to be the most important source of competitive advantage [1] .

Digital twin (DT) digitally replicates a physical system such as production plants, farms, buildings, or even larger systems such as smart cities or international supply-chain systems. Even though the concept is more than twenty years old, it is a widespread technology only in the last years due to Internet of Things (IoT) technology, making DT sustainable for many industries. As a key enabling technology with the characteristics includes interactive feedback between digital space and physical space, data fusion and analysis, iterative optimization for decision-making, the digital twin (DT) has been a research hot spot of intelligent manufacturing [2]–[4]. There is huge confusion about the concept of DT, in fact it is usually associated with concepts like simulation, cyber-physical systems, and Internet of Things (IoT). Recent scientific review papers have most of elements that make up the definition, in common: it is a virtual entity that fully represents a physical entity through its entire life cycle, thanks to real time communication [5]–[8]. This means that DT is not a simple simulation but it evolves thanks to the continuous communication with its physical counterpart so it can be used to monitor, control, optimize and check future behaviors of the latter.

In order to be able to respond quickly to unexpected events without central re-planning, future manufacturing systems will need to become more autonomous. Autonomous systems are intelligent machines that execute high-level tasks without detailed programming and without human control. In order to make this happen, the autonomous systems will need access to very realistic models of the current state of the process and their own behavior in interaction with their environment in the real world [9]. Autonomy provides the production system with the ability to respond to unexpected events in an intelligent and efficient manner without the need for re-configuration at the supervisory level. Lastly, ubiquitous connectivity such as the IoT facilitates closing of the digitalization loop, allowing the next cycle of product design and production execution to be optimized for higher performance. To achieve autonomy or self-one, a DT platform should be based on a KBS that, for the high specific characteristics, consists in a complex knowledge system that includes different concepts and models of human (manufacturing) knowledge to better fit with all human-centric cognitive processes, for example the ones involved in a standard manufacturing Enterprise Information System (EIS) or in a factory Cyber-Physical System (CPS). Hybrid modelling considers different modelling techniques, and it aims to avoid the use of only one single type of model. It is unequivocal that sustainable manufacturing needs an appropriate digital information system that has (or that is design with) an awareness of the enterprise's objectives and the impact of its use by the enterprise's resources. Today it is required that this awareness is increasingly comprehensive and effective, in other words, that it follows the 5.0 vision by making use (or being able to make use) of all 4.0 technologies.

The aim of this research is investigating systems of hybrid models and how to structure such systems in order to design an efficient DT integrated with Industry 4.0 technologies and according to the Industry 5.0 paradigm. Hybrid model systems have recently been adopted in several domains, even if the definition provided in literature is limited to considering only the integration (hybridization) between physics based and data driven models. An important open point concerns how to integrate the so-called domain and heuristics knowledge and how to structure a framework that provides for the addition of new knowledge sources over time [10]. The main scientific contribution that this work seeks to bring, therefore, is a proposal for a design method that promotes hybrid thinking, i.e., integrating different models, separately and simultaneously, to obtain more reliable descriptions and predictions of the state of the system, ensuring greater resilience of the system as it is able to exploit the strengths of different prediction models.

In order to discuss such frameworks, the next section introduces a state of the art regarding KBSs, DTs and hybrid models. Following, the second section proposes the framework based on a Hybrid KBS (HKBS) while the third section is a treatment about Industry 5.0 aspects of the proposed framework. Finally, the fourth section generally describes the application of the framework on the resistance spot welding process, before the final section about conclusions and future works.

2. State of the art

Hybrid modeling is the process of making use of two or more modeling techniques belonging to different philosophies or methodologies and then synthesizing the results into a single score or spread. The main works on this topic use the following terms: "hybrid modeling", "grey/gray-box", "incorporating external information", "knowledge-based modular networks", and "semi-mechanistic model structures" [11]. Hybrid modeling is conceptually similar to ensemble modeling but, while the seconds are referred to unify different models of the same family, hybrid modeling is referred to completely different approaches of modeling with a consequent increasing in term of complexity of managing heterogeneous characteristics. The spectrum of modelling techniques used by the literature are the mechanistic modelling and the data-driven one. The construction of a mechanistic model for hybrid modelling frameworks depends on the available prior knowledge. These mathematical statements can be expressed more simply as algebraic equations or, with increasing complexity, as ordinary differential equations, or differential algebraic equations. By increasing the complexity of the mechanistic model, one reduces the structural mismatch between the model and analyzed process, but the larger number of parameters can lead to an unsuitable model if there is not a way to reasonably estimate said parameters (this is the bias-variance trade-off for mechanistic models). The first wave of scientific papers on hybrid modelling, mainly used data-driven techniques to fill in the gaps of knowledge in mechanistic models, such as unknown nonlinear behavior (e.g., kinetics) or unknown parameters suspected to have a complex dependency on the process variables behavior. Currently, as data-driven modelling becomes a main paradigm of the fourth industrial revolution, an opportunity arises to apply them not just as a complement to mechanistic models, but as one of the main family of modelling techniques and approaches.

Finding the right hybrid model structure is fundamental. In the classical hybrid modelling literature, the prevalent way to combine the two modelling approaches (mechanistic and data-driven) starts from an analysis of the structure of mechanistic model and its assumptions, where a parallel configuration can compensate for mechanistic structural mismatch, but if the mechanistic structure is accurate enough, then a serial configuration is usually a better choice [11]. In the serial structure, the "white box" (mechanistic model) and the "black box" (data driven method) are combined in such a way that one provides an input for the other (use a neural network to estimate a parameter or use a mechanical equation to calculate a feature for inference). In the parallel structure, usually the mechanistic prediction power limited due to limitation in describing some effects is improved by the data-driven model. Surrogate models (or substitute models, or meta-models, or response surface models) are simpler mathematical representations of more complex models. They require less computational effort to be run than the more rigorous representations and have been extensively used in process modelling and optimization. These models are designed to yield unbiased predictions of sampled or simulated data which is useful to generate regular measurements in complex systems.

Combining the hybrid modelling and the DT concept, recent works can be found in the literature. Langlotz et al. propose a hybrid DT that uses both a physics-based and data-driven model, applied to energy management of manufacturing systems [12]. Other works incorporate production and machine tool prior knowledge with AI techniques to address deficiencies (e.g., uncertainties from industrial environments) of machining processes [13]. Yang et al. presents a hybrid approach that couples a mechanistic model and a data-driven method used to predict performance degradation of the transmission system of a CNC machine [14]. These are examples of DT models based on the hybridization with two models that bring better performances compared to the single ones.

3. Digital Twin based on a Hybrid KBS (HKBS)

The IT platforms at the base of the DT is not treat in this work but, in the 4.0 era, it is assumed able to allow the DT to be integrated to other Enterprise Information Systems (EISs) like Manufacturing Execution System (MES), Enterprise Resource Planning (ERP), Product Lifecycle Management (PLM) and eventual other systems specialized for Total Quality Management (TQM) and Total Productive Maintenance (TPM) or, more specifically, Predictive Maintenance. Industry 5.0 section, starting from Industry 4.0, underling AI e so DTs [15]–[18]. For the development of a DT, knowing the status of the physical component means assessing, monitoring, and evaluating such status. Such function is the same as a set of KPIs and for this reason a DT is assumed as a KBS with the aim of estimating, not only measuring, such KPIs and with the capability of considering all information processes allowed by a 4.0 CPS. The purpose of this work is to discuss the use of hybrid modeling in KBSs such as the DT, to focus attention on the different types of knowledge models that can be employed and, to propose a framework for such a KBS based on state variables, or features, of the DT and hybrid models linking some features considered as predictors to others considered targets or KPIs. This framework leaves aside the discussion of the information subsystem and autonomous functionality of a DT, but it is a human DSS in the form of a clear description of the physical component in real-time and in every other hypothetical scenario in which this component could be, and, consequently, a clear objective functions of any optimization criteria to allow a certain degree of autonomy of the DT. Along the paper the term Hybrid Digital Twin

(H-DT) is used referring to a Hybrid-Knowledge Based System (HKBS) using the hybrid knowledge modeling approach.

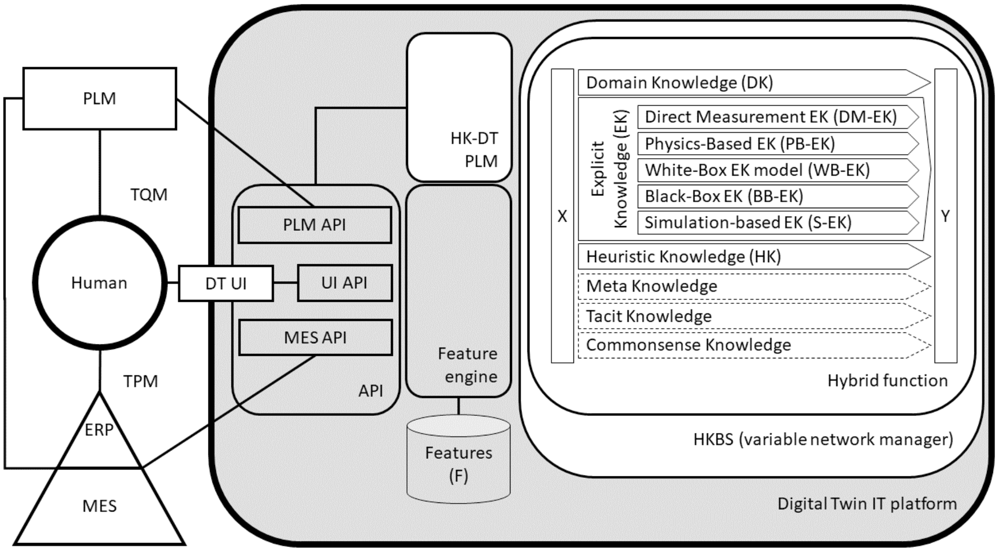

Fig. 1. Hybrid-Knowledge Based System for a product or process Digital Twin platform.

Figure 1 reports the general scheme for integrating a product or process DT in the factory CPS, giving a generic description of the role of such DT in the internal information flow of a 4.0 plant. The scheme in the figure provides an idea of the information exchange between such integrated sub-systems [15]–[19] and how a product DT has the main information flow with product-oriented platforms, like one for PLM, or how a process DT with a process-oriented one, like a MES. The DT "senses" and actuates, so interact, with the external factory information systems dedicated Application Programming Interfaces (APIs) for the DT User Interface (DT-UI) and other two APIs dedicated respectively to the MES (or ERP system) and the PLM system. In case of lack of a PLM system or of a MES (or ERP system), the two APIs with PLM and MES are assumed like PLM or MES (or ERP) platforms. All the API system interact with a feature engineering module that has the role of cleaning, extracting, standardizing, selecting, and managing the information provided by the monitoring activity of the DT (sensing) and store all this information in a "feature database", i.e., a KBS with the aim of managing available features describing the status of the physical resource to which the DT is dedicated. The feature engineering module includes a general management function of Data Quality Assessment (DQA) that considers a minimum of one KPI, mainly concerned to veracity, that is at least based on a measure of the reliability and on an indicator that measures how much the KPI is affected by the human activity. Finally, it is clear that such module concerns the management of optimization of the problem dimension, i.e., the optimization of the use, often optimizing the numbers, of features applied by different models of knowledge.

The Hybrid Knowledge Based sub-System (HKBS in the figure) of the DT consists of a software that manage the connections of the available features, linking them with hybrid functions, i.e., multivariate functions $Y = f(X)$, where each feature can be, at the same time predictors (independent X variables) and targets (dependent Y variables) of one or more hybrid function, and each model f consists in a (better if real-time) composition of functions (or knowledge edges) that came out from different knowledge modeling areas. The KPIs of the DT are, with this approach, target variables managed by the HKBS that acts like manager of historical data processing and KPI values estimation in the current, future, and alternative scenarios. The HK-DT PLM, i.e., the module that manages the lifecycle of the KBS at the base of the DT, uses the HKBS to manage the structuring and the desired real-time retraining of the learning process using inference, physics, expert knowledge, simulations, and standards together to assess the state of a physical entity at a specific time and under specific conditions.

The HKBS allows to overcome the strong connection between DT and simulation methods that, in this manuscript, are introduced simply like one of the five methods of explicit knowledge. In this way, talking about a DT as a KBS, it is necessary to consider different types of knowledge. For this reason, the knowledge generation models considered by an hybrid function module in order to estimate any status of the physical resource connected to the DT and list always by the Figure 1 are the following ones, and they are divided into five families where the most interesting one, from an engineering point of view, is the family about explicit knowledge, in turn divided into five types of methods including simulation.

- Domain Knowledge (DK) developed by specialists and experts (such as international standards)
- Heuristic Knowledge (HK) derived from personal experience (human wisdom)
- Tacit Knowledge (TK) that is knowledge stored in subconscious human mind and not easy to digitize (insights, emotions, mental models, values, and actions)
- Commonsense Knowledge (CK) is the general purpose common one
- Explicit Knowledge (EK), which refers to the knowledge that can be easily expressed and shared in the form of data, scientific formulae, product specifications, manuals, and universal principles and it can be further divided into
  - Direct Measurement (DM-EK) performed by automatic sensors or human with measure tool
  - Physics-Based (PB-EK) approach like mechanical models or chemical ones
  - White-Box (WB-EK) or Small-Data driven (SD-EK) model which usually provides a good trade-off between accuracy and explainability [20]
  - Black-Box (BB-EK) or Deep Learning (DL-EK) modeling, and
  - Black-Box (BB-EK) or Deep Learning (DL) modeling, which can be further classified into [21]
  - Simulation-Based (SB-EK) generation like Discrete Event Simulation (DES) or Finite Element Method (FEM)
- Meta Knowledge (MK), i.e., the knowledge about the proposed hybrid knowledge structure

4. H-DT supporting Industry 5.0

Industry 5.0 does not substantially involve any new technology or methodology, but it underlines how the use of the most advanced technologies risks being ineffective or, worse, unsustainable if there is no application criterion that considers the interests of the entire ecosystem. Indeed, innovation ecosystems need to be governed, and cannot be left alone to their own course [22], [23]. The decisions concerning the selection of conceptual frameworks that inform innovation ecosystem governance are important because they influence what, why, where, how, and for whom the innovations materialize or not. Industry 5.0 is about building complex and hyper-connected digital networks without compromising the long-term safety and sustainability of an innovative ecosystem and its constituents.

The centrality of the human being lies in the HK, which represents one of the main methods of generating knowledge on the state of the system to be integrated with the other kinds of knowledge through hybridization. In this way, in such a system the human has a central active role providing heuristic, domain and, if the system adopts dedicated instruments, tacit knowledge. On the other hand, the CPS has to have the following innovative features and functionality:

- supply the percentage or other metrics that indicate how much some decision is based on human-centric knowledge and how much is based on knowledge generated by other information sources
- develop a predictive model consisting in an Explainable Artificial Intelligence (XAI) that clearly shows its knowledge foundations to humans (main decision makers)
- deliver User Interface services with a correct cognitive load, leaving to the users (humans) the possibility to be concentrated only on critical decisions
- CPS has to be easy to be reprogrammable by all the involved humans like a support for the lean continuous improvement but always centered on each specific human acting in the system

Sustainability, on the other hand, is addressed through the principles of smart data and ease of integration with the other information system present in the company. Retroactively, in fact, the H-DT can evaluate the use of only the data strictly necessary for the system, finding the right trade-off between managing the large amount of data provided by 4.0 technologies and the use of small data which, however, often do not guarantee the levels of accuracy necessary for the production of knowledge able to optimize manufacturing processes. As regards the ease of integration, the H-DT gives the necessary freedom to design a digital system customized to the needs of the factory in such a way that it can be both a single platform (composed of various micro-services) that carries out all the functions necessary for management, and a platform that can be integrate with the information systems already present in the company in order to provide the functions that these cannot perform. Finally, such a DT model has to be applied in estimating different KPIs in order to assess and optimize the process according to different sustainability aspects, and not only the economical one.

Finally, the resilience of the system is provided through the H-DT ability to generate new types of knowledge. Furthermore, the H-DT can be extended to include new elements without modifying the existing structure to satisfy the need to insert new manufacturing resources, new production processes or new methodologies and paradigms in factory activity. The H-DT can enable Industry 5.0 to overcome technical issues by identifying them at a faster speed, identify items that can be reconfigured or renewed on the basis of their productivity, making predictions at a higher accuracy rate, predicting future errors, avoiding huge financial losses. This type of smart architecture design enables organizations to realize economic advantages successively and more quickly than ever before. H-DT can also be used to generate simulation models, access real-time computational data so that companies can remotely modify and update physical objects [13]. Finally, H-DT can be used for customization that can improve the user's experience of their product needs, a purchasing process that enables clients to build virtual environments to see the results. Information processes to extract new type of Explicit Knowledge from Tacit Knowledge (assumed unstructured). Application in welding processes

The implementation of hybrid digital twins in the manufacturing industry can offer numerous advantages, including cost, time, and resource savings in manufacturing operations. Particularly, maintenance activity assumes a significant role in this context. In fact, by ensuring the desired availability of components or systems, minimizing waste, reducing material usage, and optimizing energy consumption, maintenance fulfils the requirements of sustainability and efficiency according to the Industry 5.0 paradigm [24]. An application area, among many others, of the H-DT can be found in welding processes. Welding, and especially fusion welding, is a very complex process due to the many factors involved. Potential faults drastically degrade the mechanical characteristics of the welded structures' quality, increasing the risks of component fatigue and failure [25], [26].

4.1. Example of Total Productive Maintenance in RSW

The concept of H-DT developed in this work can play a pivotal role in the Total Productive Maintenance of Resistance Spot Welding (RSW) process. By leveraging advanced sensors, data analytics, machine learning algorithms and human expertise, H-DT can predict potential failures or defects, enabling timely maintenance interventions to prevent costly disruptions and ensure optimal performance [27]. Because of this, in the context of welding, H-DT offers important potential to foster efficient maintenance and, hence, increase operational efficiency, reduce downtime, and improve overall equipment effectiveness [28]. As an example, for RSW, critical parameters such as current flow, voltage, dynamic resistance, tool (electrode) displacement, can be monitored to indirectly infer important information regarding the electrode wear and the weld quality [29].

Focusing on the electrode contact area as electrode wear indicator and, hence, as target variable, examples of Explicit Knowledge models are reported in the following.

- Direct Measurement EK (DM-EK): the prediction of the contact area can be performed with a direct measurement through a carbon imprint test. In this experiment, a metal sheet enclosed between two layers of paper is utilized. The outer layer consists of black carbon paper, while the inner layer is white paper. A full welding cycle is performed without any electric current flowing. The electrode imprints that remain on the white paper from the carbon paper represent the electrode contact area [30].
- Physics-based EK (PB-EK): the electrode contact area can also be predicted by relying on analytical models with closed-form solutions. These equations allow to estimate the peak temperature profiles within electrodes during RSW based on factors such as weld nugget penetration, sheet metal thickness, and electrode geometry. By integrating this information with materials properties data, the change in the electrode contact area can be predicted in every weld [31].
- White-box EK model (WB-EK): the electrode contact area, for instance, can be inferred through regression analysis to find a relationship between the target variable and some explanatory variables. As an example,

the decreasing slope of the electrode displacement signal during welding can be used to explain the variation of the contact area throughout the electrode wear process [32].

- Black-Box EK (BB-EK): the contact area can also be predicted by employing multiple predictive variables related to the target. A representative example is the Neural Network adopted in [32], where multiple features from the electrode displacement signals are used to predict the electrode contact area.
- Simulation-based EK (S-EK): a finite element model can also be employed to simulate the RSW process and analyze the behavior of the electrode contact area which, in turn, can be used to create a lumped parameter model. Such a model can be fine-tuned through calibration using dynamic resistance curves obtained during the welding process. By means of that, a recursive estimation procedure can be devised for the prediction of the electrode contact area, considering different values of RSW process parameters [33].

However, other types of knowledge can also be adopted to make reliable predictions of the electrode contact area.

- Domain Knowledge (DK): for instance, it is possible to follow the recommendations of different standards, such as AWS D8.9 M [30].
- Heuristic Knowledge (HK): the experience of the operator, in case of non-automatic RSW station, can provide valuable insights for the assessment of the electrode contact area based on the sound emitted during welding, the number of sparks, and so forth.

4.2. Example of Total Quality Maintenance in RSW

A further development that goes beyond preventive maintenance or electrode wear prediction is the introduction of the H-DT to merge and analyze information from maintenance activities, destructive and nondestructive tests, thermo-mechanical simulations, reference standards, monitoring systems, etc. to provide the operator with a DSS tool to act on current situation and predict future events.

Taking as target the nugget size in RSW, Explicit Knowledge (EK), with practical examples, can be explained as:

- Direct Measurement: either destructive testing (optical microscopy) or nondestructive testing (computed tomography, scanning acoustic microscopy [34], magnetic characterization [35], infrared thermography [36]).
- Physics-Based: Zhou ed al. [37] developed a mathematical model to assess the nugget growth process based on the weld’s heat energy.
- White-Box: algorithms which are classified as “white-box”, such as regression, can be used to predict the nugget diameter [38].
- Black-Box: neural networks (NN) cam be employed to predict the nugget size, as was done in [39].
- Simulation-Based: Finite Element Method (FEM) based software, such as Sorpas®, can be used to estimate the nugget dimension [40].

Regarding the other types of knowledge, the following examples can be made:

- Domain Knowledge (DK): as mentioned in 5.1, the use of standards related to RSW could help to reach the desired nugget size [30], [41], [42].
- Heuristic Knowledge (HK): the operator’s experience, as already explained in 5.1.

5. Conclusions and future works

The results of this paper are general concepts on the architectural definition of a complex CPS such as a DT. The DT is a KBS that needs increasingly complex models as the complexity of the product or processes considered increases. Digital services of this kind need to be able to draw on the technical and scientific knowledge of human beings, but at the same time make use of IoT systems in order to increase performance in decision supporting. Additionally, for technologies such as DT, an unexplored source of knowledge is that human knowledge that is difficult to structure, Tacit Knowledge, which, however, thanks to the complete digitization of processes, can be considered digitizable and therefore employable to provide increasingly accurate and precise estimates even in the case of production scenarios far from those known and observed. According this manuscript, the DT is a complex paradigm included in other Enterprise Information Systems (all DTs refer to products and processes managed by the PLM and the MES, but for not all products and processes digitally managed by an organization a DT is needed) and, for this reason, it includes, in addition to simulation models or a few others of Explicit Knowledge, all the knowledge that even more complex systems such as PLM systems and MESs are capable of handling (though not capable of autonomously extracting valuable information from such knowledge sources). For these systems, therefore, it is not interesting what types of models to employ, but how to employ as many as possible and what hybrid model structures (parallel, sequential, based on voting strategies or more complex structures) need to be designed in order to build a Decision Support System (DSS) that uses so-called Smart Data [11] in order not only to ensure performance in terms of accuracy and precision, but in accordance with the vision of the Industry 5.0 society.

Summarizing, this work proposes (i) the conceptual division between product and process DT to differentiate the problems related to TQM and PLM from those related to production management and TPM, (ii) a clear classification of the types of knowledge models that can be employed by providing a sub-classification as far as it concerns Explicit Knowledge (currently the one of greatest scientific interest), and, finally, (iii) a description of the new performance requirements promoted by Industry 5.0 for technologies such as DT. This work does not deal in depth with the description of the system of features, i.e., state variables, KPIs and predictors on which this DT is based, but in any case, gives guidelines on how this structure will be set up in future works.

Future works have the aim of deeply analyzing the requirements, the structure, and the benefits provided by hybrid DTs. In particular, it is interesting to describe in detail how a product DT integrates with PLM platforms in order to improve production quality, while, on the other hand, it is equally interesting to study how such systems can support Predictive Maintenance starting from similar works [43], [44], already present in the literature. Other further works should be regarding the treatment of KPIs of such DT, i.e., which are common ones for all product and process DT applications and how to deliver to humans or automatic Decision Support Systems (DSS) a confidence metrics that measures how reliable are the estimations provided by the KBS. Working on this principle, it is interesting to study what is the best way to categorize sources of uncertainty and describe how they affect such reliability. In the 5.0 era, it is of even greater interest to study how to measure the influence of human activity on the measurements and estimates committed to DT and, consequently, how that source of variability affects system performance. The measurement of human influence falls under the study of heuristic, tacit and commonsense knowledge, which use various human cognitive processes as sources of knowledge generation in accordance with the principle of human centrality in the context of Industry 5.0.

This work is a first step toward formalization of the knowledge structures on which a DT is based. This KBS is considered as a system designed to provide the most accurate and comprehensive description of the state of a physical resource under different scenarios: future or alternative ones. This concept supports any decision-making process involving the physical resource, but it does not address how to structure the autonomy ability of the DT, i.e., how to make the DT a DSS capable of suggesting decisions or implementing those decisions autonomously. After describing the information infrastructure of the DT and describing the hybrid framework that manages knowledge generation, an interesting future work is to define an additional layer of the DT that works employing such knowledge and reliability indicators in order to make the DT autonomous in making decisions. This level will therefore be the one that will mainly take the concept of DT from the 4.0 era to the 5.0 one: the ability to make decisions autonomously, in fact, make the DT a full-fledged Artificial Intelligence (AI) that, in accordance with the European vision, considers in its decision-making processes the concepts of human-centrality, resilience, and sustainability in terms of economy, environment, and society.

Finally, as with almost all modelling techniques applied in manufacturing, a valuable contribution for the scientific community is to provide open data on which to test such complex methodologies. Such data must allow the application of all described model families to compare the performance between them and test the benefits of applying a hybrid approach. In general, providing open data is a necessary practice that ensures the replicability of scientific work. The application of different models on the same dataset certainly provides the basis for an excellent comparison between them but does not guarantee the portability and generality of the methodologies used. A final further future work, therefore, is to apply these methods to different use cases such as, for example, milling processes compared with welding ones or, why not, to apply these methodologies to very different use cases such as, again for example, the management of a teaching activity where the product DT corresponds to the student's DT and the process DT corresponds to the DT of the course or of the tools applied in it.

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