Data Fusion perspectives for Digital Twin implementation

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Abstract: The Digital Twin (DT) is a key concept for the implementation of Cyber-Physical Systems (CPS) in manufacturing, which is one of the main elements of Industry 4.0. It represents a virtual counterpart of a physical entity and can be used to simulate distinct scenarios based on models, input data and sensor information. In the virtual space, data analysis allows to make predictions and optimizations in the model, which could lead to the performance improvement of a product or process in the physical twin. Data is the core element that interconnects the physical and virtual worlds. In a manufacturing process, several data are generated through sensors and machines. A relevant aspect is related to the ability of the system to deal with a large amount of multi-source heterogeneous data (e.g. virtual space, physical environment, historical databases) and its variety issues (e.g., inconsistent data, sensor failures, data compatibility). Therefore, efficient methods should be employed to increase data reliability. In this sense, data fusion is a technique that combines multiple sources in order to improve data quality, extract relevant information and aid decision making. So, the aim of this research is to conduct a quantitative analysis to investigate the employment of data fusion and its correlated terms applied in the context of DT, assisting the research community in future studies and providing support for the use of data fusion strategies.

Keywords: Digital Twin, Data Fusion, Data Aggregation, Data Combination.

1 Introduction

In recent years, the manufacturing industry has faced a global challenge of adaptation due to the increasing use and development of digital technologies (Negri et al., 2017). This is emphasized through the heightened implementation of the Industry 4.0 technologies, such as Big Data, Internet of Things (IoT), Artificial Intelligence (AI), Cyber-Physical Systems (CPS), among others (Qi et al., 2018; Tao and Zhang, 2017). In this scenario, sensors, intelligent machines, and systems are interconnected, resulting in a cooperative environment capable of exchanging information, and providing abilities of self-adaptation, self-organization, and self-learning, in order to reach smart manufacturing (Chen et al., 2017).

According to (Um et al., 2017; Wang et al., 2019), CPS is one of the essential elements for smart manufacturing. It aims to provide association mapping, interaction, and convergence of the physical world and the virtual world and, in this sense, data is the core element that interconnects these worlds (Angrish et al., 2017; Xu et al., 2018). For the CPS implementation, the Digital Twin (DT) is considered a key enabling technology (Liu et al., 2019; Qamsane et al., 2019) and it stands for an integrated system which represents a virtual counterpart of a physical entity that mirrors the operation of physical entities in order to simulate their behaviors (Cimino et al., 2019; Rosen et al., 2015), based on real-time information from sensors, input

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data, and models (Haag and Anderl, 2018). In the virtual space, the behavior of a physical entity can be evaluated, and through simulation, data analysis can be employed to predict and estimate dynamic changes in a process and/or a product (Landolfi et al., 2018; Qi and Tao, 2018). As a result, physical entities can be adapted according to the enhanced model from the virtual space (Qi et al., 2018).

In the manufacturing shop-floor, most of the data are originated from sensors and machines, and the increasing amount of multi-source heterogeneous data represents a challenge due to the nature of the applications (Roblek et al., 2016; Zhang et al., 2019). These data may be imperfect, correlated, inconsistent, and/or in different forms/modalities (Khaleghi et al., 2013). As a result, it is necessary to increase its reliability and convert the data into valuable information to support further analysis and decisions in the virtual space (Tao and Zhang, 2017). In this context, data fusion is a multilevel process that can detect, associate, correlate, and combine data and information from several sources in order to obtain enhanced information (Dong et al., 2015). With a high volume of data being collected from several sources (e.g., machines, sensors, databases, virtual space, among others) (Shi et al., 2011; Tao et al., 2019b), data fusion has emerged recently as a data preprocessing phase to support data-intensive applications (Diez-Olivan et al., 2019). Its techniques play an essential role, resolving conflicting values and finding the underlying true values, which results in a less expensive, higher quality, and/or more relevant information (Castanedo, 2013).

Therefore, this research aims to investigate the use of data fusion and its related terms applied in the implementation of DT in the Industry 4.0 context. It consists of a narrative literature review to consolidate information regarding data fusion and DT, then, a quantitative analysis is conducted to identify the employment and the main application areas regarding data fusion and DT technologies.

The rest of the paper is structured as follows. Section 2 describes the research methodology. Section 3 and 4 presents a narrative literature review of the DT and data fusion. In section 5, the quantitative results are presented based on the use of data fusion in DT and its application areas. In section 6, the conclusion summarizes and presents the relevance of data fusion for DT implementations in the context of Industry 4.0.

2 Methods

In order to build a bibliographic portfolio, a comprehensive search was performed in Scopus and Web of Science databases to identify publications associated with this topic. As the proposal is to evaluate the use of data fusion in DT implementation, the strategy adopted was not to consider the term data fusion and its related terms in the search string and afterward conduct a textual analysis to investigate its usage.

Two search axes were considered, the first related to Industry 4.0, Smart Factory/Manufacturing and Cyber-Physical Systems, and the second axis related to Digital Twin. Thus, the following search string was used in Scopus database: (“industr* 4.0” OR (smart W/2 factor*) OR (smart W/2 manufact*) OR “cyber-physic*”) AND ("digital twin*"). For Web of Science database was considered: ("industr* 4.0" OR (smart NEAR/2 factor*) OR (smart NEAR/2 manufact*) OR cyber-physic*) AND ("digital twin*"), both updated until December 2019.

The search was based on the title, abstract and keywords, and limited to English language; subject areas: engineering or computer; source type: conference proceedings or journals; and document type: articles or conference papers. Scopus database resulted in 233 documents, and Web of Science resulted in 147 documents. Then, by eliminating duplicate articles and from the analysis of the title, keywords, and abstract in order to verify its significance with the topic researched, the number of articles was reduced to 185.

3 Digital Twin

In the last few years, DT has been an object of studies in manufacturing contexts due to the diffusion of Industry 4.0 concepts and the increasing interest in the interaction and convergence between the physical and virtual worlds, also known as CPS (Tao et al., 2019b). In the Industry 4.0 context, the term DT is directly related to smart manufacturing and industrial intelligence (Peng et al., 2019), and it is considered a key enabling technology for CPS implementation.

According to (Zheng et al., 2018), DT is defined by "an integrated system that can simulate, monitor, calculate, regulate and control the status and process of the system". (Gabor et al., 2016) described DT as "a specific type of simulation, which is built on the basis of expert knowledge and real-time data collected from the system, to perform a more accurate simulation at different time and space scales". (Qi and Tao, 2018) states that DT is about "to create the virtual models for physical objects in the digital way to simulate their behaviors". Despite all the definitions of DT, in a general way, DT can be considered a virtual copy of a physical system that represents its functionalities and characteristics, so that, all types of simulation systems applied to mirror the real operating conditions in real-time, can be understood as a twin (Rosen et al., 2015).

In the context of smart manufacturing, DT is responsible for the whole process management and optimization thought the cyber-physical closed-loop (Qi et al., 2018). Based on sensory information, input data and models, manufacturing resources are allocated according to its capacities, and production plans adjusted in agreement with an improved scenario simulated in the virtual space (Qi and Tao, 2018). In the production stage, real-time monitoring and process adjustments are performed through the cyber-physical interaction and collaboration, where the virtual model is optimized based on the physical object an vice-versa, in order to achieve optimal manufacturing (e.g., accuracy, stability, high efficiency, and product quality) (Tao et al., 2019b). To minimize machinery downtime and improve its availability, predictive models are employed in the virtual space, to schedule corrective maintenance and estimate the condition or state of a system by analyzing its performance (Vathoopan et al., 2018), also known as PHM (Prognostic and Health Management).

However, there are several issues to be addressed in DT implementation. (Tao et al., 2019b) points out that one of the main aspects is how to realize an effective cyber-physical fusion, (Angrish et al., 2017) advises that integrating and linking data into a meaningful context can be challenging and expensive to implement, (Tan et al., 2019) informs that even with some proposed frameworks it is not clear what kind of data and information needs to be integrated, (Damjanovic-Behrendt and Behrendt, 2019) states that a critical pre-requisite is to have a proper data integration platform and infrastructure, (Cheng et al., 2018) describes that unreliability and uncertainty in the transmission process of the collected data generally cause some problems. As can be seen, most of the issues arise from how to manipulate data and keep its reliability. Therefore, cyber-physical integration is a critical issue that needs to be solved towards smart manufacturing.

The theoretical foundations behind DT come from areas such as information science, production engineering, data science, and computer science (Tao et al., 2019b). According to (Qi et al., 2018), DT can be applied in production planning, manufacturing execution, and equipment PHM, product design, real-time monitoring, and other areas. In (Scaglioni and Ferretti, 2018), a dynamic model of a machine tool was developed to demonstrate the cutting process and the model of the transmission chains and the control system. (Schleich et al., 2017) proposed a referential model for the product's DT with a focus on managing geometric variations. (Hu et al., 2018) describes a method for building Cloud-Based DT (CBDT) in order to reduce computing resources in the information processing center, improving the interaction between humans and cyber-physical systems. (Zhang and Ji, 2019) described a DT-driven carbon emission prediction and low-carbon control of intelligent manufacturing job-shop, including a DT model of low-carbon manufacturing, digital twin data interaction, and fusion. (Kabaldin et al., 2019) created a DT model based on a neural network to analyze the dynamic stability of a cutting machine. (Knapp et al., 2017) applied DT techniques in an additive manufacturing process to assist in quality control by predicting changes in cooling rate, temperature gradient, velocity distribution, and solidification parameters.

4 Data Fusion

According to (Catarci et al., 2019; Tao et al., 2019a), data fusion is the core driver of DT in order to process an enormous amount of data generated by sensors and provide a unified, accurate and reliable data to support DT implementation, realizing an effective integration between the physical and virtual worlds (Lu and Xu, 2019).

Researchers proposed several definitions or explanations for data fusion (Khaleghi et al., 2013; Lahat et al., 2015), one of the most accepted and widespread definition was given by the Joint Directors of Laboratories (JDL), which describes data fusion as: “multi-level, multifaceted process handling the automatic detection, association, correlation, estimation, and combination of data and information from a single or more than one sources”. Another definition was provided by (Boström et al., 2007) as “the study of efficient methods for automatically or semi-automatically transforming information from different sources and different points in time into a representation that provides effective support for human or automated decision making”. According to (Kondo et al., 2019), the association between the concepts of data fusion can be interpreted as an interaction of sets. Information fusion, data aggregation, data combination, multi-sensor integration, multi-sensor data fusion, and sensor fusion also are fundamentals concepts belonging to data fusion (Alturki et al., 2017; Castanedo, 2013).

The term data fusion is mostly used for raw sensor data, while information fusion specifies analyzed data (Castanedo, 2013), though generally these terms are employed as synonyms. Data aggregation is defined by (Cohen et al., 2001) as a mechanism for collecting raw data from different sources and transform into refined information, delivering less voluminous and better-quality data, eliminating redundancies and discrepancies. According to (Hall and Llinas, 1997), data combination is a process of fusing different types of data and from multiple sources into a higher-value data content. Sensor/multi-sensor data fusion can be defined as a collection of techniques capable of combining sensor data in order to improve its quality and accuracy (Duro et al., 2016; Mitchell, 2007). (Luo and Kay, 1990) states that the concept of multi-sensor integration is related to the use of information collected from multiple sensory devices to support the execution of a given task by a system.

Data is the central element that interconnects the cyber-physical worlds, however, merging data from multiple sources is a complex and challenging task. (Mönks et al., 2016) describes that the fusion of sensor data may not be clear, understandable, or traceable, resulting in decisions that are not always consistent. The biggest challenge is in the data to be fused, as imperfections and inconsistencies can arise in different ways (Khaleghi et al., 2013) and a key point is associated with the capacity of the system to cope with the diversity issues. In order to solve these problems, data fusion methods can be used to increase data quality and reliability. (Akhoundi and Valavi, 2010) classifies these methods as probabilistic, statistic, knowledge base theory, and evidence reasoning methods.

There are several applications of data fusion in different areas. (Davenport et al., 2010) proposes a model that obtains the correlation between the observations of a specific sensor, combining the values of the parameters for the different measured collectors. (Liu et al., 2018) also use multi-sensor data fusion to analyze cutting parameters and vibration signals in order to classify different machining conditions on a milling machine. In this same sense, (Elgharbawy et al., 2019) presents algorithms for merging multi-sensor data in automotive networks to improve the interpretation of traffic situations, assisting in inferences and decision making. (Bashi et al., 2011) demonstrates a method based on Dempster-Shafer's theory of evidence to detect machine failures and increase the accuracy of decision making by merging information from various sensors. (Qiu, 2002) based on the estimation of a common Gaussian mixture distribution, an algorithm was developed and to be applied in various industrial processes, as well as in multi-sensor networks.

5 Results

For the past few years, DT has been a relevant topic in manufacturing processes due to the evolution of Industry 4.0 concepts and CPS implementation. **Fig. 1** depicts the increasing number of scientific publications per year, from 2015 to 2019, according to the search criteria described in Section 1.

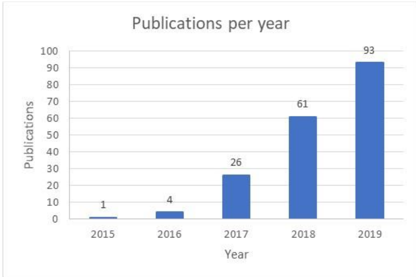

Fig. 1. The number of scientific publications per year, according to the search criteria.

Based on the articles, a textual analysis was conducted to investigate the use of a preprocessing phase to transform data into relevant information to support analysis and decisions in the DT, in the Industry 4.0 context. This analysis was centered on the term data fusion and its related terms: information fusion, data combination, data aggregation, multi-sensor integration, multi-sensor data fusion, and sensor fusion. From the total number of documents (185), 86 (46.5%) referred to one of these preprocessing techniques to support DT implementation. Among them, Multi-Sensor Integration (MSI) is described in 37.2% of the cases, right after, Data Combination (DC) is described in 36%, Data Aggregation (DA) in 27.9%, Data or Information Fusion (DIF) in 23.3%, and Multi-Sensor Data Fusion or Sensor Fusion (MSDF/SF) in 17.4%.

Regarding the DT application areas in which data fusion and its related terms are described, the applications were grouped based on four perspectives: 1) Factory and Production System Planning (FPSP), which are related to production plans and resource allocation (e.g., materials, equipment, tools, operators); 2) Simulation for Production Optimization (SPO), which involves the use of a tool or technique to simulate and optimize resources, production scheduling, machines and tools conditions; 3) Process Monitoring and Control (PMC), which are related to real-time monitoring and control, such as, equipment, machines, energy consumption, material tracking, virtual sensors, quality control; 4) Prognostic and Health Management (PHM), which involves the use of methods to predict and prevent a system breakdown, machine failures, and optimize equipment maintenance and repair. Considering this, DT applications that informed the requirement of a preprocessing phase are most related to PMC (45.3%), followed by FPSP and SPO (both with 43%) and PHM (20.9%). The percentages were determined based on the number of occurrences per document, once the terms and applications might be used with different purposes in the same article.

To summarize the findings, Table 1 demonstrates the relationships between data fusion and its related terms and DT application areas. Among the 86 articles investigated, the top 10 were listed in the following based on its significance, according to Google Scholar.

Table 1. Relationships between the preprocessing phase and DT application areas, in the Industry 4.0 context

References	Data fusion and related terms						Application areas			
	DIF	DC	DA	MSI	MSDF / SF	Context	FPSP	SPO	PMC	PHM
(Negri et al., 2017)			X			"…which are aggregated in a model…"	O	O	O	O
(Qi et al., 2018)	X					"…as well as their fusion data..."	O	O		O
(Tao and Zhang, 2017)	X	X		X		"…through data fusion algorithms…" "…through data comparison, association, combination…"; "…integrates…data from multiple sources, like sensor data…"	O	O		
(Zhuang et al., 2018)	X					"…methods to connect and fuse all the shop-floor models…"	O	O	O	

(Angrish et al., 2017)		X	X			"…combined to create the data store…"; "…algorithms that aggregate data…"			O	
(Tao et al., 2019b)	X	X		X		"…to realize data fusion, it is necessary…"; "…combined the DT with sensory materials…"; "…method to integrate sensor data…"	O	O	O	O
(Qi and Tao, 2018)	X			X		"…from the fusion operation for the data…"; "…in addition to the sensors data…integrates historical data…"	O	O		O
(Cheng et al., 2018)	X			X	X	"…iteration and fusion between the real-time…"; "…data integration from physical layer to…"; "…aspect of data fusion within WSN…"	O	O	O	O
(Lu and Xu, 2019)			X	X	X	"…data processing module aggregates…"; "…requires good integration of sensor networks…"; "…data fusion can clean, and pre-process…generated by various sensors…"			O	
(Cai et al., 2017)	X	X		X	X	"…techniques of data and information fusion…"; "…to combine these two types of sources…"; "…integrate manufacturing and sensor data into…"; "…using sensory data and information fusion integration…"	O	O		O

6 Conclusion

This article presented a narrative literature review of data fusion and DT concepts as well as application areas in which data fusion techniques and its related terms provide support to enhance data reliability and assist DT implementations, in the context of the Industry 4.0. There are still issues regarding DT implementation, and most of them are related to data manipulation and its consistency. Due to the significant amount of data handled in DT, data fusion is considered a core driver in order to convert data into useful information towards smart manufacturing. The results demonstrate that 46.5% of the articles considered the adoption of a preprocessing phase to support DT implementation. However, very few articles described how to perform the integration and the methods applied in data fusion (e.g., estimation methods, cross-covariance, aggregation methods, among others), which opens an opportunity for future studies.

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