Computers in Industry 133 (2021) 103508

Contents lists available at ScienceDirect

Computers in Industry

journal homepage: www.elsevier.com/locate/compind

Autonomous, context-aware, adaptive Digital Twins—State of the art and roadmap

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ARTICLE INFO

Article history:
Received 20 January 2021
Received in revised form 21 June 2021
Accepted 28 June 2021
Available online 13 October 2021

Keywords:
Digital Twins
Digital Factories
Context-awareness
Autonomy
Adaptivity

ABSTRACT

Digital Twins are an important concept in the comprehensive digital representation of manufacturing assets, products, and other resources, comprising their design and configuration, state, and behaviour. Digital Twins provide information about and services based on their physical counterpart's current condition, history and predicted future. They are the building blocks of a vision of future Digital Factories where stakeholders collaborate via the information Digital Twins provide about physical assets in the factory and throughout the product lifecycle. Digital Twins may also contribute to more flexible and resilient Digital Factories. To achieve this, Digital Twins will need to evolve from today's expert-centric tools towards active entities which extend the capabilities of their physical counterparts. Required features include sensing and processing their environment and situation, pro-actively communicating with each other, taking decisions towards their own or cooperative goals, and adapting themselves and their physical counterparts to achieve those goals. Future Digital Twins will need to be context-aware, autonomous, and adaptive. This paper aims to establish a roadmap for this evolution. It sets the scene by proposing a working definition of Digital Twins and examines the state-of-the-art in the three topics in their relation to DTs. It then elaborates potentials for each topic mapped against the working definition, to finally identify research gaps allowing for the definition of a roadmap towards the full realisation of autonomous, context-aware, adaptive Digital Twins as building blocks of tomorrow's Digital Factories.

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https://doi.org/10.1016/j.compind.2021.103508
0166-3615/

1. Introduction

Manufacturing companies are today confronted with increasingly global and dynamic markets. They consequently need to reshape their strategies to meet the 21 st Century's challenges concerning competitiveness, productivity, and sustainability. Examples of these challenges include shorter product lifecycles, ever more demanding customer requirements especially towards quality and sustainability, the trend towards mass customisation, as well as the necessity to establish new revenue streams via the servitization of physical products. To meet these challenges, manufacturing, supply chain management and logistics increasingly depend on interactions between all stakeholders in the product lifecycle. The heterogeneity of the resources involved, and the autonomy of the actors bind resources and demand a high level of coordination from all players, interoperating seamlessly with different stakeholders, processes, products, and resources. In addition, demands for more flexible systems that can quickly react to faults and changes throughout the product lifecycle mean that systems will need to adapt quickly and appropriately within these complex interaction environments. For example, manufacturing systems need to become more adaptable to react to fluctuations in demands, changes to product configurations or to the supply chain, and disturbances in production. IT systems in product development need to be able to easily incorporate information from stakeholders in the middle-of-life of the product lifecycle, such as usage behaviour, maintenance, and information from product-service systems. Reverse logistics systems can contribute to better sustainability by intelligently processing information from previous lifecycle phases.

Digital Twins (DTs) and Digital Factories (DFs) are two concepts which promise to help address the challenges and requirements outlined above. DTs are comprehensive, actionable, model-based digital representations not only of the form of a product, system, or resource but also of its behaviour (Rosen et al., 2015), which can include simulation or prediction. DTs can be used to plan, optimise, and simulate operations without the need for the physical entity. As realistic digital representations, DTs can serve as comprehensive sources of information about their counterparts. They can be considered the building blocks of a vision of future DFs in which product lifecycle stakeholders collaborate via the information provided by DTs. A DF built upon DTs viewed in this way can extend beyond company boundaries and offer the opportunity for the business and its suppliers to collaborate on processes that affect the entire supply chain (Bicocchi et al., 2019). By interfacing DTs with each other, they can contribute to a seamless interoperation between products, processes, and resources. DTs also hold promise to contribute to more flexible and resilient DFs. To achieve this, the DT concept will need to evolve beyond today's expert-centric tools for planning, optimisation and simulation activities (Hartmann et al., 2018) to encompass features which allow them to sense and process their environment and situation, pro-actively exchange information with each other, take decisions towards their own or shared goals, and be able to adapt themselves and their physical counterparts to achieve those goals. That means, future DTs should be context-aware, autonomous, and adaptive.

As digital representations of physical assets, DTs are related to concepts such as agents, holons, cyber-physical systems (CPS) and product avatars. Nevertheless, there are few proposals suggesting DTs may communicate with each other or their environment, or cooperate towards common goals as distributed, autonomous entities. Furthermore, not all sources explicitly mandate a direct control loop between DTs and their physical counterparts (Cimino et al., 2019).

This paper intends to contribute to the evolution of DTs by investigating their potentials in tomorrow's DF and give impetus for research toward the implementation of context-aware, autonomous, and adaptive DTs. Since the DT concept is still evolving and is used to refer to a broad spectrum of approaches, the next section proposes a working definition of DTs. Section 3 investigates the state-of-the-art of each of the topics context-awareness, autonomy and adaptivity. Since DT literature has hitherto only marginally been concerned with these topics, the state-of-the-art presented here includes work relevant to expanding the concept towards these capabilities. The fourth section looks at the potentials for context-awareness, autonomy, and adaptability for DTs. The firth section attempts to pinpoint research gaps which need to be addressed and proposes a roadmap. The last section draws conclusions from the above and highlights noteworthy trends in the future development of context-aware, autonomous, and adaptive DTs.

2. A working definition of Digital Twins

Grieves made the first recorded use of the term DT in 2003 in a course on Product Lifecycle Management (PLM) (CoBuilder, 2018). A DT was originally merely a digital representation of a physical object as a CAD model (Grieves and Vickers, 2016). The concept was expanded over time to mean an actionable simulation including not only the form of an object but also its behaviour (Grieves and Vickers, 2016), and was adopted by the aerospace industry to describe mirroring information of space vehicles (Glaessgen and Stargel, 2012) as "twin" models (Rosen et al., 2015). Here, DTs integrate sub-models of different systems and environmental interactions of a vehicle by combining stochastics, on-board sensor data and historical data sets to mirror its operational phase for health management, prognostics and diagnostics, used to estimate remaining useful life or mission success rates (Glaessgen and Stargel, 2012; Reifsnider and Majumdar, 2013). There have also been efforts to integrate physics-based models with DTs. Physics-based models offer a high degree of interpretability, reliability, and predictive capability and are commonplace throughout engineering. The integration of such models with DTs, that provide digital models tailored to each unique physical asset, addresses the main limitation of physics-based models, i.e., the assumption that the model used is an accurate reflection of the underlying physical system. Such physics-aware, or hybrid DTs (Chinesta et al., 2020) are quite useful in engineering applications in areas like aviation (Kapteyn et al., 2020), smart grid (Tzanis et al., 2020) and battery management (Sancarlos et al., 2021). The concept was transferred to production systems and smart manufacturing in 2013 (Lee et al., 2013; Lu et al., 2020). Subsequent authors extended the application area to products in general and other life cycle phases, most prominently for design and production processes (Schleich et al., 2017). Comparable concepts such as Product Avatars were developed in parallel (Hribernik et al., 2005; Ríos et al., 2015).

Usage of the term is inconsistent, for example regarding simulation. Whilst some authors equate DTs with simulations of systems (Glaessgen and Stargel, 2012; Shafto et al., 2012; Gabor et al., 2016), others view them as models to be used as a basis for different kinds of simulations (Reifsnider and Majumdar, 2013; Tuegel, 2012; Gockel et al., 1813; Hochhalter et al., 2014). This is exacerbated by the lack of comprehensive and general reference models (Lu et al., 2020; Kritzinger et al., 2018)), although models of varying degrees of detail exist for specific use cases. RAMI4.0 has been shown to be a useful pattern for defining DTs in manufacturing. In this context, DTs are increasingly being considered a part of Cyber-physical System (CPS) architectures, realising twin models of assets and machines (Josifovska et al., 2019), the computational modules of the physical components of CPS (Alam and El Saddik, 2017), or the RAMI4.0 asset administration shell (Anderl et al.,

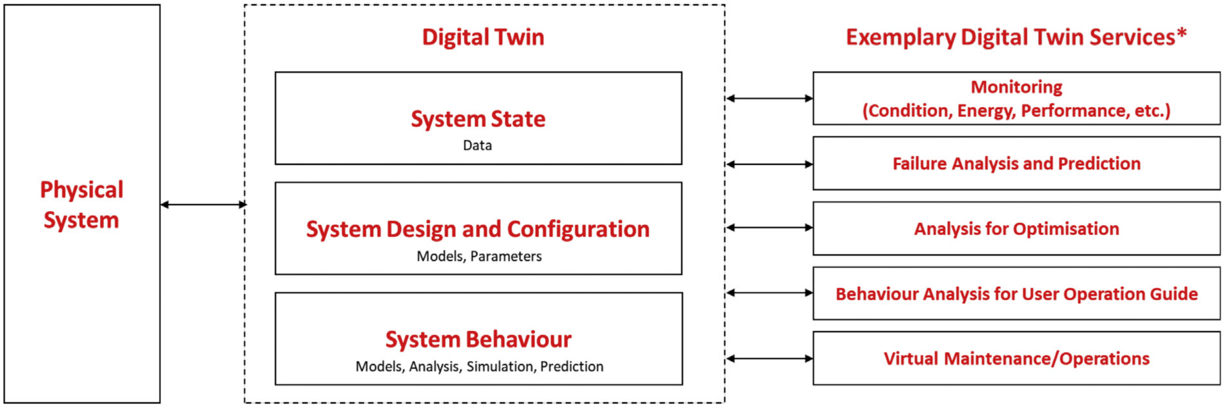

Fig. 1. Schema of a Working Definition of Digital Twins.

(* Source: (Cimino et al., 2019)).

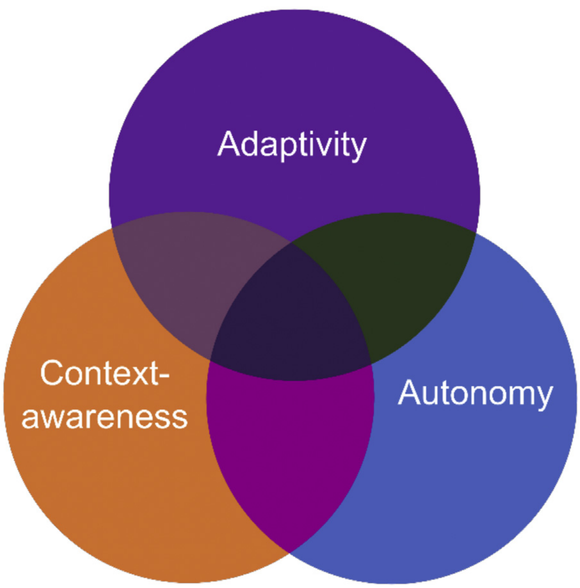

Fig. 2. Relation of the properties adaptivity, autonomy and context-awareness.

2018; Tantik and Anderl, 2017). Here, specific challenges towards information, model, system and tool integration have not yet been fully addressed (Koulamas and Kalogeras, 2018). STEP (Standard for the Representation of Product Model Data, ISO 10303 Product Data Representation and Exchange) has also been suggested as a basis for the specification of DTs (Anderl et al., 2018). Whilst these works are solid groundwork towards a reference model integrated into the Industrie 4.0 context, more work is required before the role of DTs in smart manufacturing is fully understood and defined.

Due to these inconsistencies, the following proposes a working definition of core characteristics of DTs common to most sources and aligned with the CIRP encyclopaedia definition (Stark and Damerau, 2019) and informed by (Cimino et al., 2019). DTs as understood here are comprehensive digital representations of physical assets, comprising their design and configuration, state, and behaviour, as shown in the schema in Fig. 1 below. The three core components system design and configuration, system state, and system behaviour, are elaborated in the following subsections. This paper focuses its investigation on the three core components of this working definition, considering DT services to be applications built upon this core.

2.1. System state

One unique characteristic of DTs is the (real-time) reflection of an active product's, system's, or product-service system's (Stark and Damerau, 2019) state based on sensor data (Bicocchi et al., 2018; Glaessgen and Stargel, 2012; Reifsnider and Majumdar, 2013; Lee et al., 2013; Lu et al., 2020), information from IT systems (Glaessgen and Stargel, 2012; Reifsnider and Majumdar, 2013; Lee et al., 2013), execution systems (Bicocchi et al., 2018), or other sources of usage information, like maintenance histories (Glaessgen and Stargel, 2012; Reifsnider and Majumdar, 2013). The system state is structured by ultra-realistic, high-fidelity models (see below) and thus requires a high level of digitalisation. DTs are also mentioned in literature which do not yet have a physical counterpart (e.g. a product under design), or their physical counterpart is incomplete (e.g. in manufacture or assembly) (Boschert and Rosen, 2016; Qi and Tao, 2018). In these cases, the system state component may contain data, for example, from test or manufacturing systems (Lu et al., 2020), simulation or data analysis (Qi and Tao, 2018). This way, the DT can already be used to simulate or predict the behaviour of a system before it is built, similarly to Virtual Prototypes (Madni et al., 2019). DTs which implement a control loop by reflecting the virtual system state back onto the physical counterpart are also described in literature (Bicocchi et al., 2018; El Saddik, 2018), and can even be considered to be a characteristic which distinguishes DTs from Digital Shadows (Cimino et al., 2019).

2.2. System design and configuration

The System Design and Configuration part comprises mainly static information and models about the system, ranging from simple product models, over detailed design models such as CAx or STEP supporting the dimensioning and design of parts, bills of material, to configuration and layout data and other parameters (Rosen et al., 2015; CoBuilder, 2018; Lee et al., 2013; Shafto et al., 2012; Anderl et al., 2018; Stark and Damerau, 2019; Guo et al., 2019). This part can also consist of static process models where DTs of processes or systems are concerned (Bao et al., 2019). A DT is different from conventional design models in this dimension in that it represents a specific instance of a product and a series (Madni et al., 2019). It should always reflect the characteristics of its physical counterpart. Consequently, data-driven parameter calibration and model validation are necessary and design and configuration models need to evolve dynamically over the lifecycle of the counterpart (Lu et al., 2019).

2.3. System behaviour

DTs include integrated “ultra-realistic, high-fidelity” (Glaessgen and Stargel, 2012; Shafto et al., 2012) models describing their physical counterpart’s behaviour (Rosen et al., 2015; Glaessgen and Stargel, 2012; Reifsnider and Majumdar, 2013; Lee et al., 2013). To illustrate, predicting the remaining useful life of an aircraft requires detailed modelling of its response to aerodynamic, high-frequency sonic and dynamic loads, and thermal fluxes (Tuegel and Ingraffea, 2011). In addition, simulation needs to model e.g., the history of the structure’s response to forces to analyse potential damage. This necessitates integrating many models: e.g. multi-physics and damage modelling, models for dealing with aleatory and epistemic uncertainty derived from interval theory, and high-resolution structural analysis (Tuegel and Ingraffea, 2011). Besides multi-physics and numerical modelling (e.g. 3D modelling) and simulators (e.g. finite element methods), data driven analytics is becoming increasingly relevant (Tao et al., 2019a). This assumes that since data is a manifestation of both known and unknown physical factors, a data-driven model can account for a better virtual model in a non-parametric setting and to anticipate events. Various machine learning and artificial intelligence techniques are useful for the development of data-driven models, while a recent effort tries to consistently integrate the various approaches in the overall vision of DTs (Rasheed et al., 2019).

3. State-of-the-art

Currently, no literature specifically addresses context-awareness, autonomy and adaptivity together in relation to DTs. Literature specifically addressing the application of the individual properties to DTs is also lacking. This paper consequently focuses on examining the three properties to identify their potentials for DTs. These three properties are often discussed in conjunction with one another, as illustrated in Fig. 2. For example, context-awareness and adaptivity intersect where a system’s behaviour is modified based on information about its logical, physical, and/or external context. Likewise, autonomous systems or entities may use context-awareness to take decisions based on information about their environment or situation. Autonomous entities can show adaptive behaviour when their decisions lead to the modification of the entity’s behaviour. This paper focuses on applying all three properties to DTs: DTs which are aware of their own context, capable of autonomous decision-making and adapting themselves, their physical counterparts, and by extension, the systems within which they operate.

3.1. Context-Awareness

Context-awareness is the capability of customizing the behaviour of a system or of a component depending on the context in which it executes to make it more effective or relevant to the situation in which it is being used (Lucke et al., 2008). Context is any information that can be used to characterise the situation of an entity (Alexopoulos et al., 2016), such as a person, place, or physical or computational object (Lee and Martinez Lastra, 2013). A context-aware system can access and process information which describes context. What constitutes context information can been classified in different ways. A prominent classification distinguishes primary (time, identity, location and activity) and secondary context which can be derived from the primary ones (Alexopoulos et al., 2016). These basic classes are not always appropriate for industrial applications, which can benefit from a more specific classification such as user, environment and production contexts (Rosenberger and Gerhard, 2018). Another helpful classification distinguishes between external and internal context (Alexopoulos et al., 2016). The former relates to places, people and their roles, and things. The latter describes goals, tasks, work contexts, business processes, communication, and even emotional and physical states.

Context modelling is used to organise context information, allowing, for example, to define context types, relationships, and dependencies between context information, and to control quality and consistency. Context models also facilitate reasoning on context information. Different approaches can be taken to context modelling, including graphical and object-oriented, logic-based and semantic modelling (Lee and Martinez Lastra, 2013).

Different technologies can be exploited to generate and communicate context information in manufacturing environments. Context information describing environmental parameters can be sourced, for example, from sensors and embedded systems (Alexopoulos et al., 2016; Azouz and Pierreval, 2019), RFID (Alexopoulos et al., 2016), BLE (Bisio et al., 2018), NFC (Alexopoulos et al., 2016), IoT (Alexopoulos et al., 2016; Bisio et al., 2018; Lee et al., 2016) and CPS (Alexopoulos et al., 2016). Context can also be more broadly understood to include not only the environment of sensors and embedded devices, but also the users and their preferences (Bisio et al., 2018). In manufacturing, context-aware applications may also utilise information e.g. about the planning and execution of manufacturing processes, which can be provided by IT systems such as manufacturing execution (MES) or enterprise resource planning (ERP) systems (Alexopoulos et al., 2016). This may also include a history of events related to products and resources (Azouz and Pierreval, 2019). Since the system state component of a DT reflects the status of a physical object as monitored e.g., by sensors, IoT devices and other sources, DTs can act as providers of context information to other DTs.

Context-awareness can contribute to the “smartness” of factories and manufacturing environments (Radziwon et al., 2014). By bridging the gap between the virtual and physical worlds using IoT, objects can be made recognizable and smart, and context-related decisions can be supported in a smart factory environment (Bisio et al., 2018). Examples of application areas in smart manufacturing include energy management, failure management, manufacturing cycle time optimisation, shop-floor management, and manufacturing system reconfiguration. Context-aware energy management enables users to monitor and control their energy consumption in a smart way, so they can control their utilities and equipment and adapt their behaviour in order to avoid energy waste (Lee et al., 2016). In mass production with high volumes and low profit margins, context awareness can help optimize manufacturing cycle times. It has been shown to contribute to managing high product variety and batch size variation when handling many parts, e.g. in white goods manufacturing (Alexopoulos et al., 2016). In failure management, context-awareness allows interventions to be more effective because they can be focused on what happened and in which environment (Wieland et al., 2010). Shop-floor management can be improved by context-awareness by using sensors to expose processes in a clearer way, providing the right information, to the right people, at the right time (Alexopoulos et al., 2016), supporting worker’s decisions by providing useful information in the right context (Lee and Martinez Lastra, 2013).

Making DTs context-aware will contribute to a *more holistic representation of their physical counterparts* including their environment and execution context (Borangiu et al., 2019), which is helpful for e.g. HRC applications, where a robot’s position needs to be considered in relation to humans. Context-awareness in DT literature is found mainly in CPS-related research relating to **the system state** component. An early approach to context-aware DTs in CPS *includes context information in the representation of the system state* of a production plant, via a separate context-aware application (Park et al., 2020). In this case, the DT itself is not fully context aware.

DTs *can contribute to processing context information generated by CPS*, since CPS generally focus on the physical layer of embedded systems (Leng et al., 2019). They have also been proposed to *improve the identification of relevant contexts in smart manufacturing systems* (Preuveneers et al., 2018). *DTs should also act as context information sources for other networked DTs*, allowing them to process information about their environment, an important ingredient for distributed, autonomous decision-making. DTs should also be able *to access appropriate data sources based on context changes*.

A physical counterpart's context may require changes to its configuration, affecting the DT's **system design** component. For example, a machine tool might need to be configured to carry out a specific task (changing moulds or tools). The DT should be able to *understand the context to reflect this in its design models and configuration* appropriately. For example, a DT architecture for cloud-based cyber-physical systems supports *context-aware self-reconfiguration* of manufacturing systems to increase the resilience of manufacturing systems, applying fuzzy rules and Bayes networks to the system context (Alam and El Saddik, 2017). This *contributes to production system adaptivity*.

To realise context-awareness, DTs must incorporate context models into their **system behaviour** component, including models of system tasks, processes, objectives, and operations. They must access knowledge about their context, or include models reflecting their operational context. Graph-based models can represent components involved in smart manufacturing processes along with their relations, constraints and paths (Zheng and Sivabalan, 2020). This allows the DT to apply context-aware cognition to its tasks. A context model which includes the states of all objects, e.g., machines, tools, production processes, material, in a production facility has been integrated into DTs which constitute a "social factory", that is a smart factory which focusses on the interactions between people and the production environment (Kassner et al., 2017).

3.2. Autonomy

A dictionary definition of autonomy is *"freedom from external control or influence; independence"* (autonomy, 2021). More specifically, it is *"the ability to act with some measure of independence, and to assume responsibility for one's own resources and behaviour"* (Steiner, 2008). From a technical perspective, *"[a]gent X is autonomous from agent Y to the degree that X pursues its goals without input from Y"* (Müller, 2012). More autonomy implies less control (Müller, 2012), qualifying *"freedom from external control"* above. Entities may have varying degrees of autonomy and be subject to inverse degrees of external control.

Autonomy can help handle disturbances, changing market demands or other unforeseen events by shifting decision-making to smaller organizational units, which can contribute to increasing the system's flexibility and adaptability to changes or disturbances (Hülsmann and Grapp, 2005; Antsaklis et al., 2021). Resources may be autonomously reconfigured, restructured or rescheduled to continue production with minimal downtime (Park and Tran, 2011). Autonomy also helps tackle very unstructured or complex environments which cannot be appropriately anticipated (Pachter and Chandler, 1998) since shifting decision-making to smaller units breaks the total complexity of the system down to partial complexity (Hülsmann and Grapp, 2005). Decentralizing decision-making allows for a problem decomposition which reduces computational effort (Schuldt et al., 2011). In very complex systems, linear planning and scheduling can be difficult, and optimization can take considerable effort (Gebhardt et al., 2011). Autonomous systems alleviate these difficulties by reducing the need for a-priori planning and optimisation by local decision-making (Hülsmann et al., 2009). This makes autonomy an interesting approach for systems about which little is known in advance.

Smaller organisational units need to receive and process information about their environment to take their own decisions (Scholz-Reiter et al., 2021; Scholz-Reiter, 2004). Realising autonomy thus requires linking the physical to the virtual world hosting IT capable of autonomous decision-making. Technologies such as smart or intelligent processes, IoT, CPS, and indeed DTs, support this link (Maes, 1993).

Autonomous decision-making is often modelled on biological systems, for example, how humans or animals perform control tasks, recognise patterns and make decisions (Passino, 1995). Examples of these methods range from simple due date (Windt et al., 2010), queue-length estimation and rule-based approaches (Gebhardt et al., 2011) through fuzzy control, fuzzy supervisory control, fuzzy learning control, knowledge-based control, neural networks and genetic algorithms (Passino, 1995). Many methods of decision-making in autonomous systems rely on the interaction, cooperation or competition of individual units (Hülsmann and Windt, 2007). The dynamics of such an interaction *"can lead to emergent structure or emergent functionality"* (Maes, 1993). Emergent behaviour may be Predicted Desirable (PD), Unpredicted Desirable (UD), Predicted Undesirable (PU), or Unpredicted Undesirable (UU) (Grieves and Vickers, 2016). Desirable behaviour is, for example, an increase in the robustness of the overall system due to distributed and flexible handling of dynamics and complexity (Hülsmann and Windt, 2007). DTs can help manage emergent behaviour, guarantee obtaining PD, eliminate PU, and decrease UU behaviour (Grieves and Vickers, 2016). Methods supporting this kind of decision-making include swarm intelligence approaches (Mullen et al., 2009) such as ant algorithms (Gebhardt et al., 2011) and bee foraging algorithms (Windt et al., 2010), Distributed Logistics Routing Protocol (DLRP) (Scholz-Reiter et al., 2008), Link-state internet routing protocol (LSIRP), asynchronous teams (Talukdar et al., 1998), holonic manufacturing algorithms (Windt et al., 2010), or auction algorithms for decentralized parallel machine scheduling (Attanasio et al., 2006).

Autonomous systems not only need to be able to react to changes in their environment, but also to act proactively with respect to their own purposes. A proactive and anticipatory system contains "*a predictive model of itself and/or its environment, which allows it to change state at an instant in accord with the model's predictions pertaining to a later instant*" (Nadin, 2017; Louie, 2010). Proactive computing is currently understood as an evolution away from interactive computing, towards human-(un)supervised pervasive computing scenarios (Tennenhouse, 2000). Proactivity extends reactivity, referred to in literature as sense-and-response (Elwany and Gebraeel, 2008) or detect-and-act (Tao et al., 2014) – to a new model of situational awareness with four phases: Detect, Predict, Decide, Act (Engel et al., 2012). "Detect" deals with monitoring and detecting current indicators. "Predict" uses those indicators to forecast when the system will leave an admissible state if nothing changes. "Decide" takes real-time decisions about how best to eliminate or mitigate the problem and remain in an admissible state. The "Act" deals with the actual implementation of that action. Proactive event-driven architectures combine advanced event processing with dynamic forecasting capabilities leveraged towards online optimisation and decision-making (Lindberg, 1990). The decisions are made in real time and require swift and immediate processing of big data, that is, extremely large amounts of noisy data flooding in from various locations, as well as historical data (Bousdekis et al., 2015, 2017; Bousdekis et al., 2019; Petersen et al., 2016).

DT characteristics lend themselves to implementing autonomy and are already considered core enablers of autonomous systems (Cronrath et al., 2019; Rassolkin et al., 2019). However, current literature describes DTs as expert-centric tools without autonomous capabilities (Hartmann et al., 2018), and their evolution towards active components which extend the characteristics of their physical counterparts is not yet complete (Saracco, 2019; Dambrot, 2021). The **system state** component *links the physical and virtual worlds*, which is a basic requirement for realising autonomous entities. A *full control loop* is required for the DT to autonomously control its physical counterpart. Here, principles of autonomous control, both reactively and proactively, may be applied. Agent, holon or CPS principles may inspire the implementation of DT autonomy. First considerations towards the convergence of DT and CPS, formalised in the RAMI 4.0 Asset Administration Shell, exemplify this (Wagner et al., 2017).

With regards to **system design**, based on simulations and analysis in conjunction with real-time and historical data about physical assets, DTs could *autonomously take decisions about the product design and configuration* and *influence future product design* iterations (Lützenberger et al., 2016; Klein et al., 2019]. The *configuration of the physical counterpart* can also be influenced by the DT in this way (Wuest et al., 2013). In predictive maintenance, the DT may take *autonomous decisions with regards to maintenance*, affecting the physical configuration of the asset (Hribernik et al., 2018).

The advanced simulation and analytical capabilities offered by DTs' **system behaviour** component, fed with high-resolution real-time system state data and extended by context-awareness allows more accurate predictive capabilities, which can *improve autonomous decision-making in industrial scenarios* (Rosen et al., 2015). Furthermore, context-awareness could allow DTs to *autonomously select, integrate, and execute appropriate physical, simulation, and analytical models*. For example, different physical models are required for a spacecraft travelling in a planet's atmosphere or in space (orbital mechanics models).

3.3. Adaptivity

Adaptivity is the capability to modify a system or component's behaviour depending on unpredicted situations to achieve one or more goals. It describes how well a machine or group of machines can adapt to change, which can be measured by comparing the weighted flexibilities of two situations occurring at different points in time (Mandelbaum, 1978). Adaptivity is an objective of Industrie 4.0 and Cloud Manufacturing (Qu et al., 2016) and a core characteristic of smart factories, defined as a *"manufacturing solution that provides such flexible and adaptive production processes that will solve problems arising on a production facility with dynamic and rapidly changing boundary conditions in a world of increasing complexity"* (Radziwon et al., 2014).

Adaptivity involves monitoring the state and/or environment of the system or component whose behaviour is to be changed. Relevant information can be sourced in real-time, e.g. from IoT, Industrial IoT systems or CPS (Qu et al., 2016; Bergweiler, 2016). Suitable decision-making mechanisms are required to enact adaptivity once a system state is detected that requires modification. Examples include case-based reasoning (Peruzzini and Pellicciari, 2017) and decentral decision-making based on autonomous entities as described above (Gonçalves and Peschl, 2018; Sanderson et al., 2015).

Adaptivity has been applied to different manufacturing problems. For example, it can help manage increasing complexity and unpredictability. By monitoring and identifying machine status in real time, maintenance can be appropriately triggered and production rescheduled via dynamic scheduling mechanisms (Mourtzis et al., 2014). Decentralized, autonomous approaches have been shown to enable the dynamic reconfiguration of manufacturing systems, increasing flexibility, adaptability to change, and fault tolerance (Gonçalves and Peschl, 2018). Where decision-making and control of a manufacturing system are too fast, frequent, complex, or unpredictable for human intervention at run-time, adaptivity based on MAS (multi-agent systems) can help manage industrial control systems with the required speed (Sanderson et al., 2015). Small-scale adaptivity realised by context-aware distributed, autonomous CPS which monitor themselves can also help ensure and optimize production quality. By storing information about quality and process execution in each product's own CPS-enabled memory, deviations can be detected directly in the production line and corrected accordingly (Bergweiler, 2016).

In smart manufacturing, the detection of sensor or actuator outliers that deviate from the expected parameters as modelled may either indicate a fault in the sensor/actuator or a change in the process. Once a decision is made between these two options, models may need to be adapted to reflect the change. A rapid (e.g. discarding historical data before the change) or gradual (e.g. exponential forgetting) approach can be used to facilitate self-adaptive modelling to address this problem (He and Wang, 2018). Adaptivity can also contribute to dynamically organising supply chains in multi-organisational collaborations and thus optimising production (Radziwon et al., 2014), or dynamically on multiple levels for production logistics synchronisation, using Cloud Manufacturing in combination with IoT to dynamically synchronise logistics plans and collaborations (Qu et al., 2016).

Changing systems to meet the needs of workers is another significant area of application, and is fundamental to efficient and effective smart manufacturing systems (Peruzzini and Pellicciari, 2017). For example, aging workers may have different profiles of physical and cognitive limitations, restricting their ability to work at standardised workplaces. A methodology has been proposed to self-adapt manufacturing systems to their needs (Peruzzini and Pellicciari, 2017). User interfaces and information provision in manufacturing can also be adapted to workers' needs. Humans tend to behave in nondeterministic, flexible ways and adapt themselves to changing environments (Joo and Shin, 2019). This means that HMI (human–machine interaction) should be designed to provide them with the appropriate level of information depending on different system states (de Visser and Parasuraman, 2011; Inagaki, 2003). An example is preventing mode confusion, where humans work with mental models about a process that conflicts with those of involved machines, or receive confusing feedback from their user interfaces (Joo and Shin, 2019).

DT adaptivity may refer to the capability of the digital representation, the physical counterpart, or both, to adapt. Regarding **system state**, literature highlights DTs' potential to *optimise or modify their counterparts' control parameters* based on awareness of their current operation conditions (Tao et al., 2019a). For example, DTs using adaptive algorithms can *change production system control configurations* ensuring safe operations when faults occur (He et al., 2019). Context changes can trigger the DT to *modify data sources for an optimal reflection of the physical asset*. For example, changes to the stakeholder network of a Digital Factory may require the DT to access new enterprise systems or disconnect no longer relevant ones. The DT should thus *autonomously recognise the need, discover appropriate data sources, and (disc)connect those sources*. Another interesting example is represented by robotic work cells. As the tool of iterative refinement is calibration, its effective and systematic execution has to be ensured (Erdős et al., 2020). Since data can be collected continuously from the real work cell, relevant information can be stored historically. When the DT model parameters are out of the feasible tolerance region surrounding the real measurements on the physical system, they need to be adjusted. The DT should thus autonomously recognize such a divergent situation and automatically recalculate the parameter values.

Relating to **system design**, DTs can be considered *adaptive models of complex physical systems* (Rasheed et al., 2019). Context-aware changes to the physical counterpart's configuration and consequently its DT may be required, requiring the DT to *select, modify and configure models* appropriately in accordance with the situation they represent whenever changes occur. Modifications can be human-supervised or automatic. The changes can concern different aspects of the production cycle, e.g. products, services, stakeholders, and the general context. Here, a technical barrier is *adapting models to avoid discrepancies over time*, e.g. due to degradation. Model updating schemes have been put forward to facilitate adaptive models in DTs (Lu et al., 2019; Wang et al., 2019).

An adaptive physics-based performance model has been used in a DT of aero-engines to generate fault signatures that can be compared with measured flight data to assess the engine conditions (Zaccaria et al., 2018). DTs can contribute to the dynamic adaptability of manufacturing execution systems, performing *real-time optimization* of products and production processes (Zhang et al., 2017). Machine learning has been put forward as a way for DTs to adjust **system behaviour** with minimal need for supervision (Madni et al., 2019). Context may influence the parameters of or necessitate new physical, simulation and analytical models. On one level, adaptation influences the physical counterpart's configuration, depending on the goals defined by the models. The models do not change, but trigger adaptation. On a higher level, context change may require model modification: models representing the physical counterpart should be modified or replaced. Self-ware models can be used which understand when and how to modify themselves (Schaumeier et al., 2012).

Adaptive interaction with DTs is also considered in literature, with adaptive user interfaces proposed which learn the preferences and priorities of their users in different contexts and change accordingly (Madni et al., 2019, 1982).

4. Research and development gaps

This section identifies the research and development gaps to be bridged to realise the potentials of DTs summarised in Table 1.

Fig. 3 below shows a roadmap of identified research challenges towards context-aware, autonomous, adaptive DTs. It is read from top to bottom, left to right. It shows one line for each issue and a separate one for general issues. Research gaps are shown at the intersection of these lines with those of the identified research topics and are as described in the following.

The first line deals with **interoperability**. To enable the potentials of context-aware DTs, context information must be integrated into the system state component. A general issue here is maturation research towards its *harmonization with the IoT paradigm*. The role of DTs in IoT needs to be better understood, as well as which IoT protocols are appropriate for DTs. This is a prerequisite e.g. for including third party data sources into DTs. Further maturation of OPC-UA as a core protocol of Industry 4.0 may contribute to solving this issue (Jaekel et al., 2020). The establishment of DFs built on networked DTs will require a comprehensive approach to inter- and intra-factory, supply chain and lifecycle-wide interoperability. Approaches in the intelligent CPS field to monitor physical processes, create a virtual copy of the physical world and make decentralized decisions (Lu, 2017) can be exploited for this purpose. However, such approaches need to be revisited and extended to be useful for DTs interoperability. Indeed, whilst the CPS concept focusses more on sensors and actuators and the integration and collaboration of computing, communication and control, DTs emphasise models and data (Tao et al., 2019b), and go beyond CPS in their incorporation of the system behaviour element, with simulation and prediction outside of the scope of the core CPS concept. Therefore, combining DTs with semantic interoperability approaches such as mediation (Shani et al., 2017), the Industrial Data Space reference architecture (Otto et al. (2018)), or Industrial Ontologies Foundry (Kulvatunyou et al., 2018) are promising avenues of investigation. Underlying these interoperability issues is the need for work on *standards and protocols* for DT information exchange. The breadth of information, model and technology heterogeneity and the use of DTs in different sectors makes standardization for DT interoperability extremely challenging.

The next line deals with **modelling**. The model-based nature of DTs means that *context models need to be incorporated* to use context in combination with other models on the level of system behaviour. This is a significant step towards enabling autonomous, adaptive DTs. DTs capable of understanding and acting upon context will be able to *identify, connect to and collaborate with other DTs sharing their context*. Several DTs in a common manufacturing context within a production line could join together to form an autonomous, adaptive virtual production line. Research towards understanding how individual DTs may connect and collaborate is required. Agents, holons and CPS are furthermore good examples of how autonomous decision-making can be modelled and implemented based on digital representations of physical entities (Giret and Botti, 2004). *Their relation to DTs* has however not yet been studied deeply (Rosen et al., 2015); these paradigms can also contribute to understanding general issues such as the required *granularity of mapping of DTs to physical counterparts* and *managing emergent system behaviour*. Due to the complexity of the system of systems created by networking DTs, promoting PD and UD whilst mitigating undesirable behaviour will be challenging. Again, *investigating and adapting methods successfully applied in the fields of MAS and HMS* can contribute to solving this problem. Concepts such as resource, operational and product holons (Van Brussel, 2014; Leitão et al., 2003) and product agents (Främling et al., 2003) need to be looked at in this light. Agent-based and Holonic Manufacturing Systems (HMS) have successfully shown how digital representations of physical entities can autonomously cooperate in a manufacturing context towards common goals (Giret and Botti, 2004; Botti and Giret, 2008; Wang and Haghighi, 2016) and can help understand how systems of *networked DTs may be organised* e.g. as agent heterarchies/holarchies.

An issue regarding adaptivity is the definition of mechanisms for the *translation of business goals into actionable plans* that the physical counterpart can carry out and can adapt in response to unexpected situations. Methods and corresponding models are required to achieve this translation, to realise the potentials of DTs to act autonomously and adaptively within the context of higher-level business goals. A further open issue is *modelling interaction between networked DTs for cooperation and collaboration*. Agent interactions are complex to manage, so simpler models might be more appropriate for DTs. DTs represent physical systems which may change over time. The models used to represent them need to reflect these changes. Appropriate *evolving, dynamic and traceable models* are required. Research in this field exists but more work is necessary (Lu et al., 2019). Another general issue is that r*eference models for DTs* are lacking and a comprehensive framework is required to facilitate full-stack solutions and avoid fragmentation.

A final general research gap regarding modelling relates to the abovementioned standards and protocols and reference models. The work towards *full integration of the DT concept with RAMI 4.0* wrt. AAS and its convergence with CPS must progress to reinforce its potential in smart manufacturing and Digital Factories.

The third line of research deals with DT **human interaction**. At the intersection with context-awareness, research is also required as how to appropriately *represent humans in context models used by DTs*. *Borders between DT and human autonomy* must be investigated to ensure DTs have as much autonomy as possible without sacrificing human agency. This involves investigating workplace safety, psychological factors of workers' motivation, and the lim-

Table 1
Identified Potentials.

	System State	System Design	System Behaviour
Context-Awareness	• Identify relevant contexts • Process context information • Incorporate context information • Provide context information • Context-aware data sources selection • Include third party data sources	• Context-aware configuration of physical counterparts • Understand context and reflect it in design models • Support design and configuration adaptability	• Integrate rich context models • Include physical, logical, and external context models • Include models of tasks, objectives, and operations
Autonomy	• Context support for autonomous control • Proactive/reactive autonomous control • Autonomous networked entities	• Feedback loop to design • Feedback loop to configuration • Feedback loop to maintenance	• Advanced, multi-model simulations in autonomous decision-making • Context-aware, autonomous selection, integration, and execution of physical, simulation and analytical models
Adaptivity	• Context-aware data source adaptation • Control parameter adaptivity • Control configuration adaptivity	• Adaptive models of complex systems • Design and configuration model adaptivity	• Real-time system adjustment and optimisation • Context-aware model adaptivity • Context-aware behaviour model adaptivity • Self-aware, self-modifying models

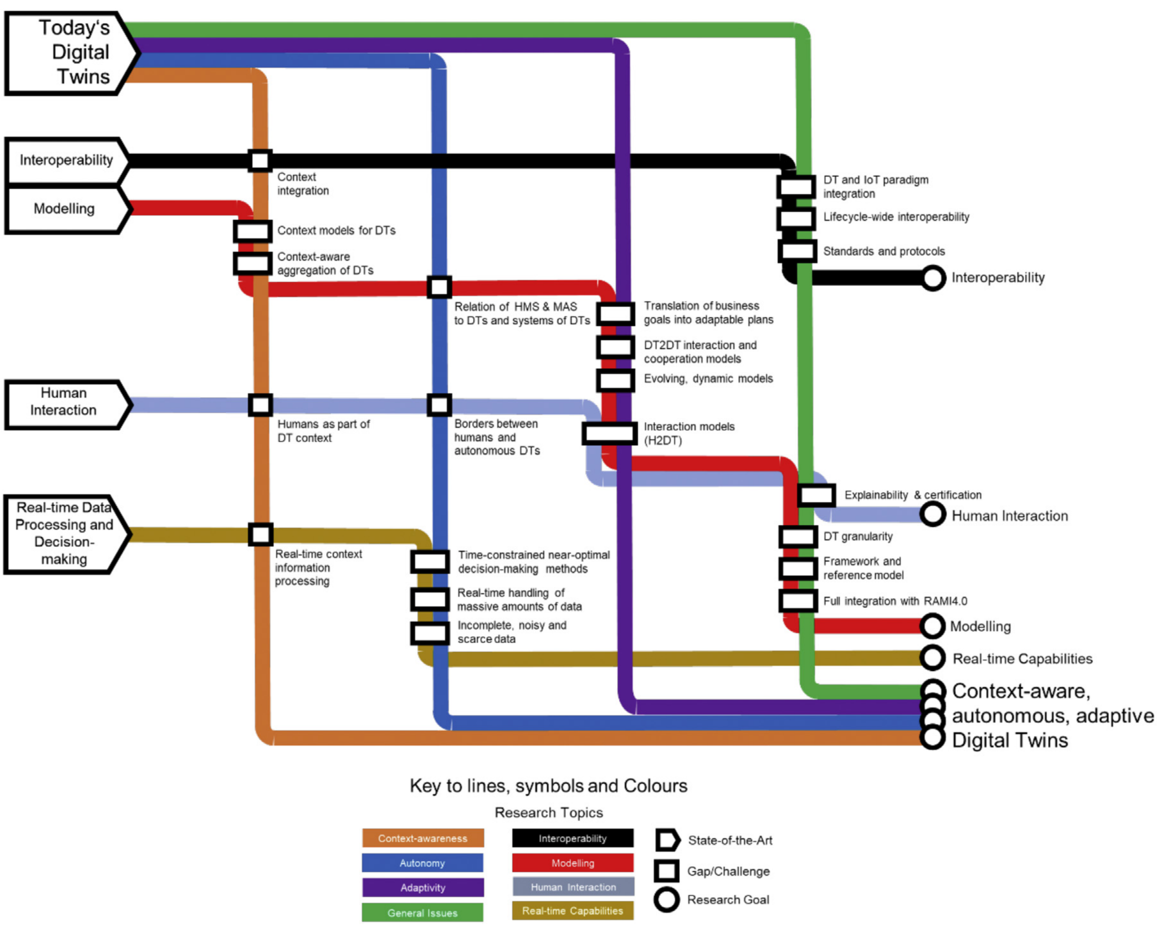

Fig. 3. Roadmap of Research Challenges.

itations of AI decision-making, etc. To effectively interact with humans in production, DTs need to be able to understand and predict the behaviour of humans working alongside them in different roles. Touching on adaptivity, *Human-to-DT Interaction Models* are required which consider different humans' profiles and how and by what medium interaction is appropriate. CPS too aim to include humans in the control loop of autonomous systems (Fantini et al., 2016) and the solutions proposed in this field represents a good starting point to address these issues. Specifically, solutions at the interface level represent the manufacturing space through Virtual and Augmented Reality based on multitouch and voice control (Gorecky et al., 2014). More visionary concepts discuss cognitive intelligent assistants using voice or even brain wave interfaces (Schirner et al., 2013). With respect to the control strategy, distributed manufacturing scheduling control paradigms have been proposed which integrate the human decision-maker's preferences into the control process (Gaham et al., 2015). Finally, DT models, simulations and predictions need to be *explainable* and, in some cases, *certified* for widespread industrial adoption, especially in safety and security-critical human-machine interaction applications.

The final research line deals with issues of **data processing for real-time, proactive decision-making**. DTs will need to *acquire context information in real-time* to enable real-time decision-making and self-aware, self-modifying models capable. Developments e.g. in ultra-low latency 5 G context-aware applications may inform these developments (Nunna et al., 2015). Real-time, proactive decision-making itself requires *methods for making time-constrained near-optimal decisions*. This might dictate the use of approximation techniques and could entail autonomic actions, rather than only providing recommendations for humans. Furthermore, massive volumes of historical data and streaming data need to be handled and analysed in real-time to forecast events, which will require new methods. Most current systems cannot handle big data in real-time because of scalability problems, the need to cleanse *noisy data* offline, or difficulties in fusing heterogeneous data types and sources online. Most analyses are today done on offline data, which means new approaches need to be developed. In contrast, *data scarcity* can result in problems of epistemic uncertainty, where a lack of knowledge can lead to difficulties in simulating or predicting system behaviour. Approaches to tackling epistemic uncertainty include incorporating expert knowledge, and applying interval theory (Wang et al., 2018). Methods of one and few-shot learning may also be applied to tackle this problem (Zhang et al., 2019).

5. Conclusions

Context-aware, autonomous, adaptive DTs have the potential to constitute the building blocks of tomorrow's DFs by supporting complex interactions via a multi-layered integration of the information related to various activities throughout the factory and the product lifecycle. Specifically, the vision of a Digital Factory architecture (Cardin, 2019) where DTs wrap physical entities involved and interact in an intelligent dataspace of diverse and distributed data sources can significantly reduce the complexity in the coordination and planning of supply chains, manufacturing systems and product lifecycles.

The potentials of these DTs outlined above can enable the aggregating analyses of data exchanged throughout the product lifecycle, succinctly reflecting an up-to-date model of their operational states. In appropriately reflecting and predicting system behaviour and acting autonomously, they can proactively adapt manufacturing, supply chain and product lifecycles processes in anticipation of changes, probable faults, and fluctuations. This would contribute to more resilience of the overall system, ready to both capture new business opportunities and successfully deal with sudden issues that may negatively impact processes.

As described in the potentials, a Digital Factory architecture built from context-aware, autonomous, adaptive DTs which could autonomously cooperate or compete to achieve common goals, realising many of the benefits of context-awareness, autonomy and adaptivity. However, the research gaps outlined above need to be addressed in a systematic way to achieve the appropriate technological maturity to achieve this goal. The following, final section proposes a roadmap of future research and development work to reach that maturity.

Declaration of Competing Interest

The authors report no declarations of interest.

Acknowledgements

This work is partly funded by the European Commission project H2020 UPTIME "Unified Predictive Maintenance System" (768634), the European Commission Marie Skłodowska-Curie Research and Innovation Staff Exchange (MSCA RISE) project FIRST "vF Interoperation suppoRting buSiness innovation" (734599), and the H2020 project DIH4CPS "Fostering DIHs for Embedding Interoperability in Cyber-Physical Systems of European SMEs" (872548).

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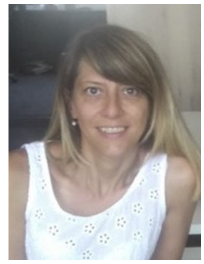

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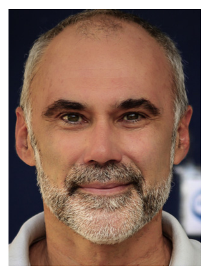

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