

## Digital twins in smart farming

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### ABSTRACT

Digital Twins are very promising to bring smart farming to new levels of farming productivity and sustainability. A Digital Twin is a digital equivalent of a real-life object of which it mirrors its behaviour and states over its lifetime in a virtual space. Using Digital Twins as a central means for farm management enables the decoupling of physical flows from its planning and control. As a consequence, farmers can manage operations remotely based on (near) real-time digital information instead of having to rely on direct observation and manual tasks on-site. This allows them to act immediately in case of (expected) deviations and to simulate effects of interventions based on real-life data. This paper analyses how Digital Twins can advance smart farming. It defines the concept, develops a typology of different types of Digital Twins, and proposes a conceptual framework for designing and implementing Digital Twins. The framework comprises a control model based on a general systems approach and an implementation model for Digital Twin systems based on the Internet of Things—Architecture (IoT-A), a reference architecture for IoT systems. The framework is applied to and validated in five smart farming use cases of the European IoF2020 project, focussing on arable farming, dairy farming, greenhouse horticulture, organic vegetable farming and livestock farming.

### 1. Introduction

Modern agricultural production is not possible without reliable and up-to-date information about farm operations. Farms increasingly have to rely on digital technologies such as sensing and monitoring devices, advanced analytics, and smart equipment. Agricultural production is changing fast towards smart farming systems, driven by the rapid pace of technology development like cloud computing, the Internet of Things, big data, machine learning, augmented reality and robotics (Janssen et al., 2017; Tzounis et al., 2017; Wolfert et al., 2017; Kamilaris and Prenafeta-Boldú, 2018; Zhai et al., 2020). Smart Farming can be seen as the next phase of Precision Agriculture, in which management tasks not only are based on precise location data but also on context data, situational awareness and event triggers (Balafoutis et al., 2017; Wolfert et al., 2017). A smart farming system can be viewed as a cyber-physical control cycle that seamlessly integrates sensing and monitoring, smart analyses & planning and smart control of farm operations for all relevant farm processes ('whole farm management perspective').

In smart farming systems, farmers can monitor and control operations remotely, based on (near) real-time digital information instead of

direct observation and manual tasks on-site. Consequently, farmers are automatically informed if there is a problem, or anything is expected to go wrong. Behind their desk or smartphone, they can check the situation in the field or stable by viewing a rich digital image of the plant, animal or machine concerned. At the same time, machine learning algorithms augment the digital view with object-specific analyses and advices. Farmers can simulate corrective and preventive actions and evaluate its impact on the digital representation. Finally, the chosen intervention can be executed remotely and the farmer can use the digital view again to verify if the (expected) problem is solved. It can also be expected that this smart farm management cycle increasingly becomes autonomous, without manual intervention of the farmer anymore. In conclusion, you could say that every object in the farm (e.g. crop, field, cow, equipment) is being virtualized and can be more and more remotely controlled. A Digital Twin is an appealing metaphor to characterize this development.

Although there are several definitions of a Digital Twin - as will be dealt with later on - a Digital Twin basically is a digital equivalent of a real-life object of which it mirrors its behaviour and its states over its lifetime in a virtual space (Boschert and Rosen, 2016; Grieves and Vickers, 2017). Using Digital Twins as a central means for farm

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**Table 1**

Overview of the use cases.

Trial/ sector	Use Case (# and name IoF2020)	Use case challenge	Focal country	Chain role	Adopter type	Conventional/ Organic
Arable	1.1 Within-field management zoning	defining specific field management zones by developing and linking sensing- and actuating devices with external data	NL	Farming, Logistics	Early adopters and majority	Both
Dairy	2.2 Happy Cow	improving dairy farm productivity through 3D cow activity sensing and cloud machine learning technologies	NL	Farming	Early Adopters	Both
Vegs	4.2 Chain-integrated greenhouse production	integrating the value chain and quality innovation by developing a full sensor-actuator-based system in tomato greenhouses	SP	Farming, Logistics, Consumption	Majority	Both
Vegs	4.3 Added value weeding data	boosting the value chain by harvesting weeding data of organic vegetables obtained by advanced visioning systems	NL, AT	Farming	Majority	Organic
Meat	5.1 Pig farm management	optimizing pig production management by interoperable on-farm sensors and slaughterhouse data	BE, NL	Farming, Processing, Consumption	Both	Both

management allows for the decoupling of physical flows from its planning and control. A Digital Twin removes fundamental constraints concerning place, time, and human observation (Verdouw et al., 2015; Verdouw et al., 2016b). Farming would no longer require physical proximity, which enables remote and automated execution, monitoring, control, and coordination of farm operations. This allows for the decoupling of physical flows from information aspects of farm processes. Digital Twins can also be enriched with information that cannot be observed (or not accurately) by the human senses (e.g. sensor and satellite data) or data that are provided by other information owners. Moreover, a crucial aspect of a Digital Twin is that it can add intelligence using advanced analytics. As such, Digital Twins do not only represent actual states, but can also analyze historical states and simulate future behaviour. As a consequence, applications based on Digital Twins, if properly synchronized, enable farmers and other stakeholders to act immediately in case of (expected) deviations.

Digital Twins are very promising to bring smart farming to new levels of farming productivity and sustainability. Although Digital Twins have recently received a lot of interest, a sound basis for development and implementation is still in progress (Schleich et al., 2017; Jones et al., 2020). Especially the application to the domain of smart farming is in its infancy (Monteiro et al., 2018; Sreedevi and Santosh Kumar, 2020). There are some explorative studies and cases about Digital Twins in farm management (such as Verdouw and Kruize, 2017; Jo et al., 2018; Monteiro et al., 2018; Kampker et al., 2019; Linz et al., 2019; Sreedevi and Santosh Kumar, 2020; Skobelev et al., 2020), but especially the management aspects of using Digital Twins to plan, monitor, control and optimize farm processes need to be further studied.

This paper aims to contribute to resolve this gap by analysing how Digital Twins can advance smart farming. More specifically, the objectives are threefold:

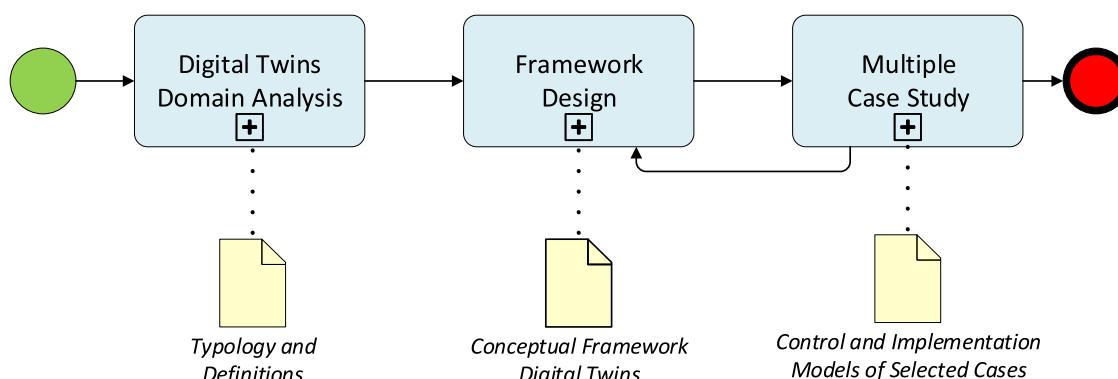
1. To define the concept and introduce a typology of Digital Twins;

2. To propose a conceptual framework, i.e. a systematic classification of concepts, for designing and implementing Digital Twins;
3. To apply and validate the conceptual framework to smart farming in a multiple case study of the European IoF2020 project.

In the remainder of this paper we first introduce the research methodology in Section 2. The next chapters describe the results of our study. The domain analysis in Section 3 defines the concept of Digital Twins, develops a typology of Digital Twins including distinct control capabilities, and introduces the usage of Digital Twins in the context of smart farming. Section 4 describes the conceptual framework developed, which comprises a control model based on a general systems approach and an enabling information architecture for Digital Twin systems. Section 5 describes the application of the conceptual framework to five smart farming use cases of the European IoF2020 project. The control model and implementation model of one of these use cases are described in more detail. Finally, the main findings are summarized and discussed in Section 6.

## 2. Methodology

The development of a conceptual framework is typically a design-oriented methodology that aims at solving a certain type of problem by constructing a new artefact (Hevner et al., 2004; Van Aken, 2004; March and Storey, 2008). The design artefact developed in this paper is a conceptual framework for the design and implementation of Digital Twins in farm management. The concept of Digital Twins is relatively new and complex. A case study is a good approach to get a better understanding of such complex phenomena, which cannot be studied outside their rich, real-world context (Benbasat et al., 1987; Eisenhardt, 1989; Yin, 2002). Hence, a multi-case study approach is adopted to evaluate the applicability of the presented framework in the context of smart farming.

**Fig. 1.** Adopted Research Methodology.

**Table 2**  
Case study design.

Case study design activity	Case study
Goal	Assessing the applicability of the Digital Twin framework in smart farming
Research Questions	How applicable is the adopted Digital Twin design approach?
Background and source	Meetings and interviews; technical reports; official project deliverables
Data Collection	Independent data collection based on document analysis
Data Analysis	Qualitative data analysis

The case study was carried out as part of the European IoT2020 project in close interaction with involved business partners (Verdouw et al., 2017). The project included 19 IoT use cases that were organized in five coherent trials that aim to address the most relevant challenges for the concerned sub sector (Verdouw et al., 2019). We have selected cases that were expected to be appropriate for illustrating the use of the Digital Twin concept, especially due to including dynamic mirroring of real and virtual objects by using IoT technologies. In total five cases were selected as being representative for different agricultural sub-sectors (Table 1).

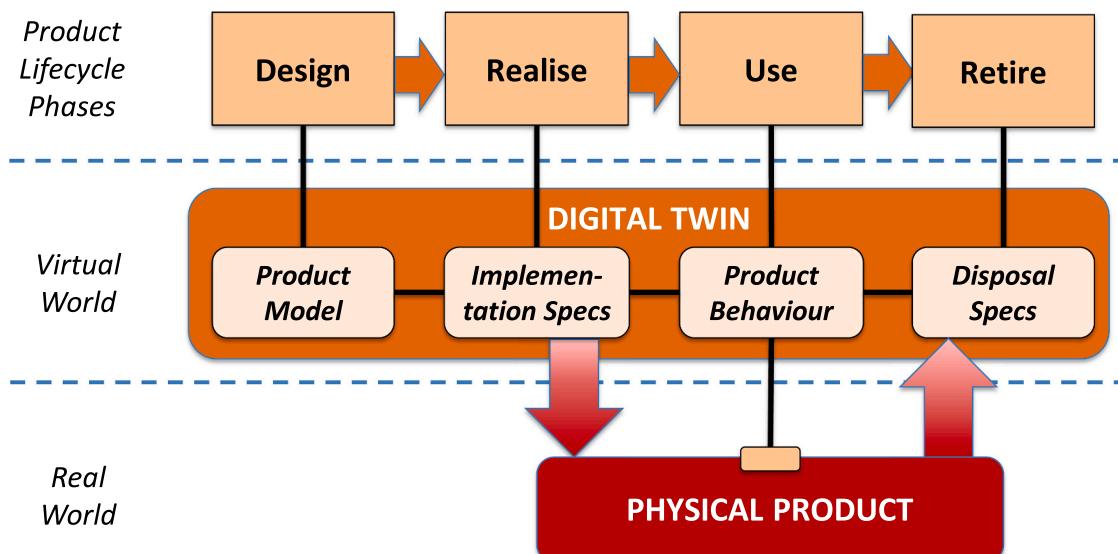
More specifically, the research was organized in three phases (Fig. 1): (i) domain analysis, (ii) framework design and (iii) application to the cases (Fig. 1).

Firstly, the research started with a domain analysis to develop key concepts based on a narrative literature review in the Scopus database and Google Scholar. We first searched for papers that include Digital Twin or Digital Twins in the title. We selected papers that thoroughly define the concept and review papers. Case studies that only mention Digital Twin without a more elaborate definition were excluded from the study. The concept of Digital Twins is relatively new and as a consequence it is used in different meanings. The definition study has therefore identified main perspectives and definitions on Digital Twins in literature, especially in the Product Lifecycle Management and Internet of Things domain. Based on this analysis, we have developed a typology of Digital Twins, including distinct control capabilities. Finally, the domain analysis has reviewed existing literature on the usage of Digital Twins in the context of smart farming. At this, we searched for papers that on the one hand include Digital Twin in the title and on the other hand agriculture or farming in the title, abstract or the keywords

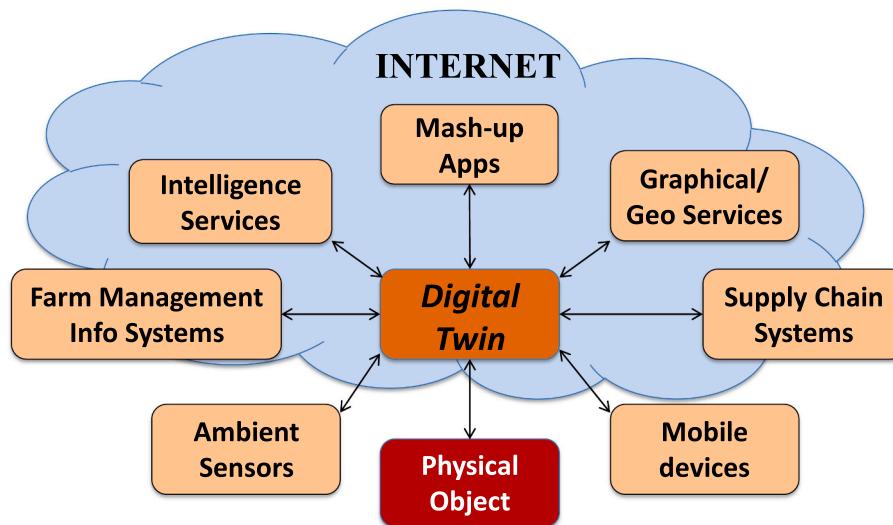
section. Non-English and non-accessible papers were excluded from the study.

Secondly, a conceptual framework was developed for designing and implementing Digital Twins in farm management. This paper focuses on providing a sound conceptual basis for the implementation of Digital Twins in smart farming, including the management aspects of using Digital Twins to plan, monitor, control and optimize farm processes. It is beyond the scope of this paper to develop a detailed reference architecture that can be used to model and realize Digital Twin-based information systems. For this reason, the framework includes two model types that represent the essence of a Digital Twin from a management viewpoint (control model) and from an information technology viewpoint (implementation model). The control model is based on a general systems approach. A control model represents the control functions needed to ensure that a system's objectives are achieved, even if disturbances occur, and information flows among these functions. Based on the literature review, the control model for object virtualization of Verdouw et al. (2015) was selected as a basis of this view. The implementation model classifies technical functionalities into different technical layers ranging from device layer to application layer, as such it provides an overview of the technical architecture. Based on the literature review, the IoT-A reference architecture was selected as a basis of this view (Carrez et al., 2013).

Thirdly, the conceptual framework was applied to cases. We have adopted the case study empirical evaluation protocol as discussed by Runeson and Höst (2008). The protocol consists of the following steps: (1) case study design (2) preparation for data collection (3) execution with data collection on the studied case (4) analysis of collected data (5) reporting. Table 2 presents the case study design steps for the selected cases. The primary purpose of the case study is to understand the applicability of the presented Digital Twin framework in smart farming. The data were collected by desk research of use case documentation and interviews with the lead architect of every use case. The interviews were conducted based on a semi-structured questionnaire comprising questions in three categories: i) use case definition, including the problem context, core idea, objective, development status, etc.; ii) use case mapping, including main business processes targeted, objects addressed, main actors using the envisaged system; and iii) use case information architecture, including the main functionalities/services to be provided to end-users, non-functional requirements, technology components envisioned, reusability, privacy/security, standards usage and available documentation. Subsequently, the researchers designed case-specific



**Fig. 2.** Role of Digital Twins during the Product Life Cycle.



**Fig. 3.** Digital Twin in the Internet of Things.

control model and technical layer models for the use cases by using the conceptual framework as designed in phase 2. The resulting case-specific models were reviewed by the use case leader and iteratively refined by the research analyst. Finally, generic implications were abstracted from the case study findings and incorporated in the framework.

The remainder of the paper introduces the results following the research steps as described above.

### 3. Definition and typology of Digital Twins

#### 3.1. What is a Digital Twin?

The principles behind the Digital Twin vision origin from the Product Lifecycle Management domain (Grieves, 2005). From this perspective, there is a strong need to integrate all product-related information in a comprehensive product management system that can be accessed by any user in any stage of the Product Life Cycle, for example for through-life performance information, design optimization and manufacturing system improvement (Philpotts, 1996; Kovacs et al., 1998; Sudarsan et al., 2005; Schleich et al., 2017). It was proposed to use a digital counterpart of each physical product as a central means to manage product data along the product life cycle. In the beginning of the century, Michael Grieves argued in a presentation to industry that a digital informational construct about a physical system could be created as an entity on its own (Grieves and Vickers, 2017). This virtual system contains all information about the physical system and it is linked with that physical system through the entire lifecycle of the system (Grieves and Vickers, 2017). NASA introduced the concept Digital Twin for this idea (Mike Shafro et al., 2012), which was an ultra-high fidelity simulation of the space vehicle that would allow the engineers on earth to mirror the precise and actual conditions of the real vehicle during the mission (Glaessgen and Stargel, 2012; Boschert and Rosen, 2016).

In essence, Digital Twins are virtual, digital equivalents of physical objects (Grieves and Vickers, 2017; Fuller et al., 2020). They are real-time and remotely connected to real objects and provide rich representations of these objects and its context. Such Digital Twins go beyond static product designs, like CAD models, but comprise dynamic behaviour (Boschert and Rosen, 2016; Grieves and Vickers, 2017). This dynamic nature of Digital Twins may include the representation of current behaviour of real-life objects, but also the simulation or prediction of future behaviour and the recollection of historical behaviour (Verdouw et al., 2015; Boschert and Rosen, 2016).

A Digital Twin can already be created in the design phase of an object's lifecycle, enhancing the creative phase of inventing new products and elaborating it into a detailed product model (see Fig. 2). In this stage, a Digital Twin allows early and efficient assessment of consequences of design decisions on the quality and function of products reducing the need to develop costly physical prototypes (Grieves and Vickers, 2017; Schleich et al., 2017). After the design phase, a physical stage is entered, in which the Digital Twin comes into existence. A physical object is produced based on the designed Digital Twin, which is updated in case of any deviations. During operational usage, the current and historical state and conditions of a physical product are monitored by using sensors and AutoID devices. Moreover, the Digital Twin can be used to remotely control an object by using actuators. Finally, the disposal phase takes place, in which the physical object is disposed, but the conceptual object may remain for some period e.g. for traceability, compliance and learning.

While originating from Product Lifecycle literature, a key technology for realizing Digital Twins is the Internet of Things (Marr, 2017). The interaction between real/physical and digital/virtual objects is an essential concept behind the Internet of Things. In the IoT, physical entities have digital counterparts; things themselves become context-aware and they can sense, communicate, act, interact with their digital counterparts and others, exchange data, information and knowledge (Sundmaeker et al., 2010). These counterparts are twins of the physical objects and can be linked to and synchronized with the physical object throughout their lifecycle (Verdouw et al., 2015; Canedo, 2016; Grieves and Vickers, 2016). The Internet acts as a storage and communication infrastructure that holds a virtual representation of things linking relevant information with the object (Uckermann et al., 2011). As such, Digital Twins serve as central hubs of object information, which combine and update data continuously from a wide range of sources, as illustrated in Fig. 3 (Verdouw et al., 2013).

The emergence of Digital Twins in literature has resulted in various definitions both from a Product Life Cycle (PLC) and an Internet of Things (IoT) perspective (see Table 3) and is discussed below.

In the IoT literature, the digital representation of physical objects using sensing technologies is highlighted. In the PLC literature, the emphasis is on mirroring real-life objects across their lifecycle, including simulation of expected object behaviour. In this paper we combine both perspectives and use the following definition: "A Digital Twin is a dynamic representation of a real-life object that mirrors its states and behaviour across its lifecycle and that can be used to monitor, analyze and simulate current and future states of and interventions on these

**Table 3**

Digital Twin definitions classified into two perspectives: Internet of Things (IoT) and Product Life Cycle (PLC); further discussion in text.

Source	Definition Digital Twin	Main perspective
Boschert and Rosen, 2016	A Digital Twin is a comprehensive physical and functional description of a component, product or system, which includes more or less all information which could be useful in all—the current and subsequent—lifecycle phases.	PLC
Durão et al., 2018	Digital Twin is a multi-physical, multi-scale and probabilistic simulation model of a complex product. It uses updated sensors and physical models to mirror physical life in the digital world and vice versa.	PLC
Glaessgen and Stargel, 2012	A Digital Twin is an integrated multi-physics, multiscale, probabilistic simulation of an as-built vehicle or system that uses the best available physical models, sensor updates, fleet history, etc., to mirror the life of its corresponding flying twin.	PLC
Fuller et al., 2020	The effortless integration of data between a physical and virtual machine in either direction.	IoT
Grieves and Vickers, 2017	The Digital Twin is a set of virtual information constructs that fully describes a potential or actual physical manufactured product from the micro atomic level to the macro geometrical level. At its optimum, any information that could be obtained from inspecting a physical manufactured product can be obtained from its Digital Twin.	PLC
Knibbe et al., 2019	Digital Twins are computational representations of both living and non-living objects and processes. They can be used to describe, analyze and simulate current and future states of and interventions in these objects, using data integration, artificial intelligence and machine learning.	IoT
Marr, 2017	A Digital Twin is a virtual model of a process, product or service. This pairing of the virtual and physical worlds allows analysis of data and monitoring of systems to head off problems before they even occur, prevent downtime, develop new opportunities and even plan for the future by using simulations. The Digital Twin is the virtual representation of a physical object or system across its lifecycle. It uses real-time data and other sources to enable learning, reasoning, and dynamically recalibrating for improved decision making.	IoT
Mikell and Clark, 2018	A Digital Twin is a digital replica of a living or non-living physical entity. By bridging the physical and the virtual world, data is transmitted seamlessly allowing the virtual entity to exist simultaneously with the physical entity.	PLC/IoT
Saddik, 2018	A Digital Twin is not one complete model of the physical product, but a set of linked operation data artefacts and simulation models, which are of suitable granularity for their intended purpose and evolve throughout the product life-cycle. Thus, the Digital Twin not only serves representation purposes but is also applicable for making predictions about the expected product behaviour, while the granularity of the simulation models fits to their purpose and evolves from early design stages, where simple product models are used to decide about product concepts, to detail design, where sophisticated simulation models support the dimensioning and design of parts and subassemblies.	IoT
Schleich et al., 2017	The Digital Twin is not one complete model of the physical product, but a set of linked operation data artefacts and simulation models, which are of suitable granularity for their intended purpose and evolve throughout the product life-cycle. Thus, the Digital Twin not only serves representation purposes but is also applicable for making predictions about the expected product behaviour, while the granularity of the simulation models fits to their purpose and evolves from early design stages, where simple product models are used to decide about product concepts, to detail design, where sophisticated simulation models support the dimensioning and design of parts and subassemblies.	PLC

**Table 3 (continued)**

Source	Definition Digital Twin	Main perspective
Shaw and Fruhlinger, 2019	A Digital Twin is a computer program that takes real-world data about a physical object or system as inputs and produces as outputs predication or simulations of how that physical object or system will be affected by those inputs.	IoT
Verdouw et al., 2015	A virtual object can be defined as ‘a digital representation of an object, with a unique identification, that can be trusted, possesses the property of integrity, is timely available, and can be used for the intended purpose’.	IoT

objects, using data integration, artificial intelligence and machine learning.” More specifically, based on literature as listed in Table 3, the following essential characteristics of Digital Twins can be addressed:

- **Timeliness:** a Digital Twin reflects its physical twin in (near) real-time, which means that state changes of the physical object are (immediately) detected and synchronized with its Digital Twin (Verdouw et al., 2015; Durão et al., 2018; Mikell and Clark, 2018; Tao et al., 2018; Knibbe et al., 2019; Park et al., 2019);
- **Fidelity:** the reliability and security of a Digital Twin must be unquestionable, allowing to blindly trust Digital Twins for decision making (Verdouw et al., 2015; Durão et al., 2018; Tao et al., 2018);
- **Integration:** a Digital Twin integrates data from different aspects of the physical object and ensures convergence in a consistent format (Schleich et al., 2017; Kritzinger et al., 2018; Tao et al., 2018; Park et al., 2019);
- **Intelligence:** Digital Twins do not only depict object data, but also include algorithms that describe, analyze or predict the behaviour of their physical twins (Glaessgen and Stargel, 2012; Schleich et al., 2017; Durão et al., 2018; Kritzinger et al., 2018; Knibbe et al., 2019; Park et al., 2019; Shaw and Fruhlinger, 2019);
- **Complexity:** Digital Twins can mirror different types of physical objects, including products, components, living and non-living resources, components and processes (Marr, 2017; Saddik, 2018). Moreover, Digital Twins may consider multiple interdependent objects as well as sub systems at different levels of granularity (Glaessgen and Stargel, 2012; Verdouw et al., 2016b; Grieves and Vickers, 2017).

### 3.2. Digital Twin typology

The focus of Digital Twins is on the usage phase of the lifecycle (Fig. 2) in which Digital Twins are connected to their real-life physical twins. During that phase, Digital Twins can be used to monitor the actual state of objects, prescribe desired states, predict future states, and to remotely correct the state of real-life objects. Before the usage stage, Digital Twins can already be created to define and simulate the states and behaviour of its real-life twins that are not yet born. Last, after the usage phase, Digital Twins will remain conceptually alive and can be used to recollect the historical states of real-life objects. As a result, we defined a typology of six distinct Digital Twins (based on Porter and Heppelmann, 2014; Verdouw et al., 2015; Hagerty, 2016; Verdouw et al., 2016b; Grieves and Vickers, 2017; Redelinghuys et al., 2019; Lepenioti et al., 2020):

- **Imaginary Digital Twin:** a conceptual entity that depicts an object that does not yet exist in real-life. It defines the information needed to materialize its physical twin including for example functional requirements, 3D product models, material and resource specifications, production models, and disposal and recycling specifications (Verdouw et al., 2015; Grieves and Vickers, 2017). Imaginary twins

can also simulate the behaviour of designed, not yet existing, objects between tolerance norms (Grieves and Vickers, 2017).

- **Monitoring Digital Twin:** a digital representation of the actual state, behaviour and trajectory of a real-life physical object. It is connected (near) real-time to its physical twin and is used to monitor its condition, operation, and external environment. A monitoring Digital Twin can be both descriptive, providing insight in what happens or happened with the connected real-life object, and diagnostic, explaining why it happens or happened by relating the object to contextual data.
- **Predictive Digital Twin:** a digital projection of the future states and behaviour of physical objects using predictive analytics, such as statistical forecasting, simulation and machine learning methods. Prediction is done dynamically based on (near) real-time data of the physical twin.
- **Prescriptive Digital Twin:** a smart digital object that adds intelligence for recommending corrective and preventive actions on the real-life objects usually based on optimization algorithms and expert heuristics. Prescriptive twins use the output of monitoring and predictive twins as an input to suggest which courses of action need to be taken to reach a favourable outcome (Hagerty, 2016). The decisions on the recommended actions still are taken by humans, who also trigger the remote or on-site execution of interventions.
- **Autonomous Digital Twin:** operates autonomously and fully controls the behaviour of real-life objects without on-site or remote intervention by humans. Autonomous twins also can become self-adaptive systems that are able to learn about their environment, self-diagnose their own service needs, and adapt to users' preferences (Porter and Heppelmann, 2014; Verdouw et al., 2016b).
- **Recollection Digital Twin:** maintains the complete history of the physical object, which no longer exists in real-life. As such, recollection twins form the digital memory of e.g. a farm. This type of Digital Twins is often neglected in literature, but it is increasingly important for reducing the environmental impact of disposals and for optimization of the next generation objects (Grieves and Vickers, 2017). In the context of farming, recollection twins are also of crucial importance for tracing products to its source in case of food safety issues and for sustainability compliance.

One should notice that the above listed properties are not independent and a Digital Twin do not necessarily belong to one category but may combine features of different types. For example, Digital Twins during the usage phase build upon each other's capabilities. An autonomous Digital Twin will typically also be a prescriptive Digital Twin, a predictive twin usually also includes predictive capabilities, and a predictive twin can also include a monitoring Digital Twin.

So far we have defined the concept of Digital Twins and introduced a typology of Digital Twins based on generic literature in the Product Life Cycle and IoT domain. In the remainder of this section we introduce the usage of Digital Twins in the context of smart farming.

### 3.3. Digital Twins in farm management

Farming is a highly complex and dynamic domain. Production processes are inherently dynamic because they depend on natural conditions, such as weather, diseases, soil conditions, seasonability and climate (Fountas et al., 2013; Trienekens et al., 2014). Moreover, farmers have to deal with critical demands from consumers and society concerning food security, food safety, sustainability and health. As a consequence, farms should not only be very efficient, but also have to meet high quality and environmental standards and should adapt to changing market conditions. This imposes high requirements on the managerial tasks of farmers (Sørensen et al., 2010; Fountas et al., 2013). They constantly have to reassess production strategies and to reschedule planned activities based on timely monitoring of farm operations in order to achieve their goals.

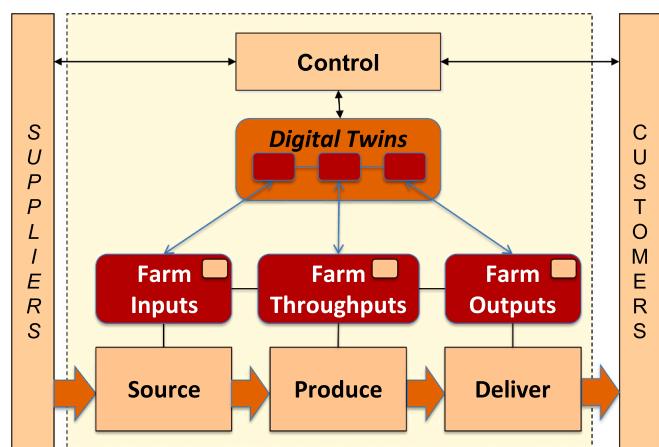


Fig. 4. Virtual control of farming enabled by Digital Twins.

As argued in the introduction section, Digital Twins can significantly enhance the needed control capabilities by enabling the decoupling of physical and information aspects of farm management (Fig. 4). However, implementing Digital Twins in farm management is a challenging task for (at least) three reasons (Verdouw et al., 2016b).

First of all, the highly dynamic production system in agriculture (process dynamics) poses requirements that go beyond many other sectors concerning the capabilities of Digital Twins to mirror dynamic behaviour. In such a dynamic environment, it is really challenging to get seamless access to object data while ensuring the integrity of data and respecting usage rights, safety and security. Furthermore, real-time synchronization can be complicated in rural areas, which often have limited coverage and bandwidth.

Second, agricultural products are living objects that inherently are diverse and are characterized by complex behaviour. Moreover, farms don't have one Digital Twin of concern for smart farming, but they are composed of a large variety of interrelated objects (object complexity). Main objects are i) inputs including seeds, feed, fertilizers or pesticides, ii) throughputs including objects in production (e.g. growing crops or animals) and resources including fields, stables, machinery and personnel, and iii) agricultural output including harvested (lots of) crops, animals ready to be slaughtered, etc. Digital Twins of a fine granularity level, e.g. up to individual plants or animals, would add more value, but are also more difficult to implement, which results in higher costs. In case of a fine granularity, a key challenge is to manage the interdependences between (sub) Digital Twins at different granularity levels.

Third, farms are part of a dynamic network and share data with many stakeholders including customers, input suppliers, farmer cooperatives, advisors, contractors, and certification and inspection organizations (network dynamics). These stakeholders may also have access to the farmer's Digital Twins, but limited to the information that they need. This implies that there must be interoperable solutions for providing external access to specific views on Digital Twins in a secure and trusted way. Vice versa, external stakeholders can enrich farm Digital Twins with a wealth of (3rd party) archives such as historical and forecasted meteorological data, satellite data, soil-, water- and air-analyses, etc. There should be proper mechanisms in place to dynamically integrate these data in farm Digital Twins.

Digital Twins can be seen as a new phase in smart farming. It is building upon existing technologies especially for precision farming, Internet of Things and simulation. As a consequence, there are multiple applications in the agricultural domain, although often not framed as Digital Twins. However, most of these applications are still rather basic forms of Digital Twins, focusing for example on digital representation in a cloud dashboard. More advanced applications, including e.g. predictive and prescriptive capabilities across the lifecycle, are still in an early

stage of development. In our literature review, we only found a few explorative studies and some case studies that frame an IoT-based system as a Digital Twin, without a detailed motivation or definition of the concept. These papers, which are discussed below, are all congress papers, except one book chapter.

To the best of our knowledge, [Verdouw and Kruize \(2017\)](#) were the first who explored the application of Digital Twins in farm management. The paper considers Digital Twins from an Internet of Things perspective, in which physical objects have virtual, digital equivalents that are real-time and remotely connected. Illustrated by six cases of the FIWARE Accelerator program, the paper shows that Digital Twins are already implicitly used in smart farming, but existing applications mostly focus on basic monitoring capabilities. The authors argue that these capabilities establish a basis for optimization, simulation and decision support based on on-line Digital Twins.

[Jo et al. \(2018\)](#) conducted a feasibility study on using Digital Twins in pig farms to improve animal welfare. They introduce three so-called Digital Twin platforms (Prefix, Ditto and Watson) and proposed a design smart livestock farming system using such a Digital Twin platform. The paper states that a Digital Twin is the digital replica of the real world, but it does not further elaborate on the concept, neither it describes how the designed system supports Digital Twins.

[Monteiro et al. \(2018\)](#) present a technical IoT-based model and a prototype to implement Digital Twins in vertical farming. Digital Twins are defined as digital mirrors of physical objects. The Digital Twin designed in the paper is envisioned to support the lifecycle of planning, operation, monitoring, and optimization of vertical farms. The focus of the prototype is on sensing and controlling the conditions via light and misting.

[Alves et al. \(2019\)](#) developed an IoT-based prototype to sense field conditions including soil moisture, air temperature and humidity, and to visualize this information in a dashboard. This prototype is called a Digital Twin, in which data flows automatically between a physical and a digital object. The authors argue that a Digital Twin enables farmers to make better decisions and to decrease the environmental impact in water, land and soil resources.

In the research of [Kamper et al. \(2019\)](#), a Digital Twin is an artificial potato, which is planted in the field and harvested just as real potatoes. The 'digital' potato is equipped with sensors that measure its treatment, especially shocks, blows and rotation speed, etc. This information is used to adjust the settings of the harvesting machine, thus minimizing damage to the potatoes. Subsequently, the digital potato is synchronized with a cloud platform to enable smart services like potato price and field revenue estimations ([Maaß et al., 2018](#)).

[Linz et al. \(2019\)](#) applied Digital Twins in the development of field robots, for example for phenotyping and crop treatments in vineyards. They simulate the autonomous behaviour of robots in a 3D environment using real-time data and mirror the simulated Digital Twin to operate the real-life robot. This results in shorter lead times of development, better evaluation of sensor behaviour and reducing the needed field experiments to evaluate phenotypes or test the effects of crop treatments.

[Skobelev et al. \(2020\)](#) propose a multi-agent approach to development of Digital Twins of plants. A plant Digital Twin is defined as "a computer model that imitates its life cycle and synchronizes with the living plant using examinations by agronomists and data on environmental conditions (weather, soil, etc.)".

Finally, [Sreedevi and Santosh Kumar \(2020\)](#) argue that there are relatively few studies about Digital Twins in agriculture compared to other domains. Furthermore, they discuss the potential contribution of Digital Twins in hydroponics farming, especially for predicting probable failures and optimizing the whole farming system, including the management of nutrients, pH values, pathogens and weeds.

Based on the domain analysis introduced above, the next section describes the conceptual framework developed for designing and implementing Digital Twins.

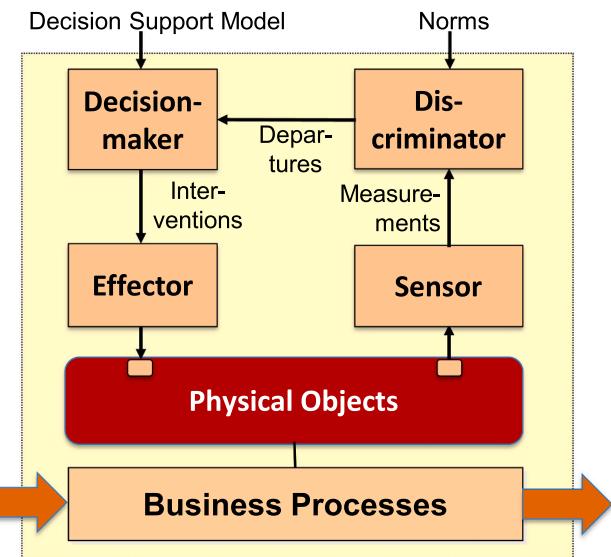


Fig. 5. Basic control model.

#### 4. Conceptual framework Digital Twins

The conceptual framework of this paper should provide a sound conceptual basis for implementation of Digital Twins in smart farming, including the management aspects of using Digital Twin to plan, monitor, control and optimize farm processes. More specifically, the following basic requirements are defined based on the literature study of the previous section:

1. The framework must address the cyber-physical control cycle of smart farming that seamlessly integrates sensing and monitoring, smart analyses & planning and smart control of farm operations for all relevant farm processes ('whole farm management perspective');
2. The framework must support the entire life cycle of farm objects and consequently it must include the six distinct Digital Twins defined, i.e. Imaginary, Monitoring, Predictive, Prescriptive, Autonomous and Recollection Digital Twins;
3. The framework must support the implementation of essential characteristics of Digital Twins, i.e. timeliness, fidelity, integration, intelligence, and complexity;
4. The framework must address the specific challenges of implementing Digital Twins in farm management, i.e. farm object complexity, farm network dynamics and farm process dynamics.

The designed framework includes two model types that represent the essence of a Digital Twin from a management viewpoint and from an information technology viewpoint. This section introduces both models: i) a control model for Digital Twins based on a general systems approach and ii) an implementation model that provides an overview of the technical architecture for implementing Digital Twins.

##### 4.1. Control model

###### 4.1.1. Farm control from a systems perspective

Control is a basic concept in system dynamics. It ensures that the system's objectives are achieved, even if disturbances occur. The basic idea of control is the introduction of a controller that measures system behaviour and corrects if measurements are not compliant with system objectives ([de Leeuw, 1997](#)). Farm processes are 'in control' if the performance of its operations remain in a steady state. Therefore, the activities of these processes must include the cybernetic control functions necessary to demonstrate 'cybernetic validity'. Basically, this implies that they must have a feedback loop in which a norm, sensor,

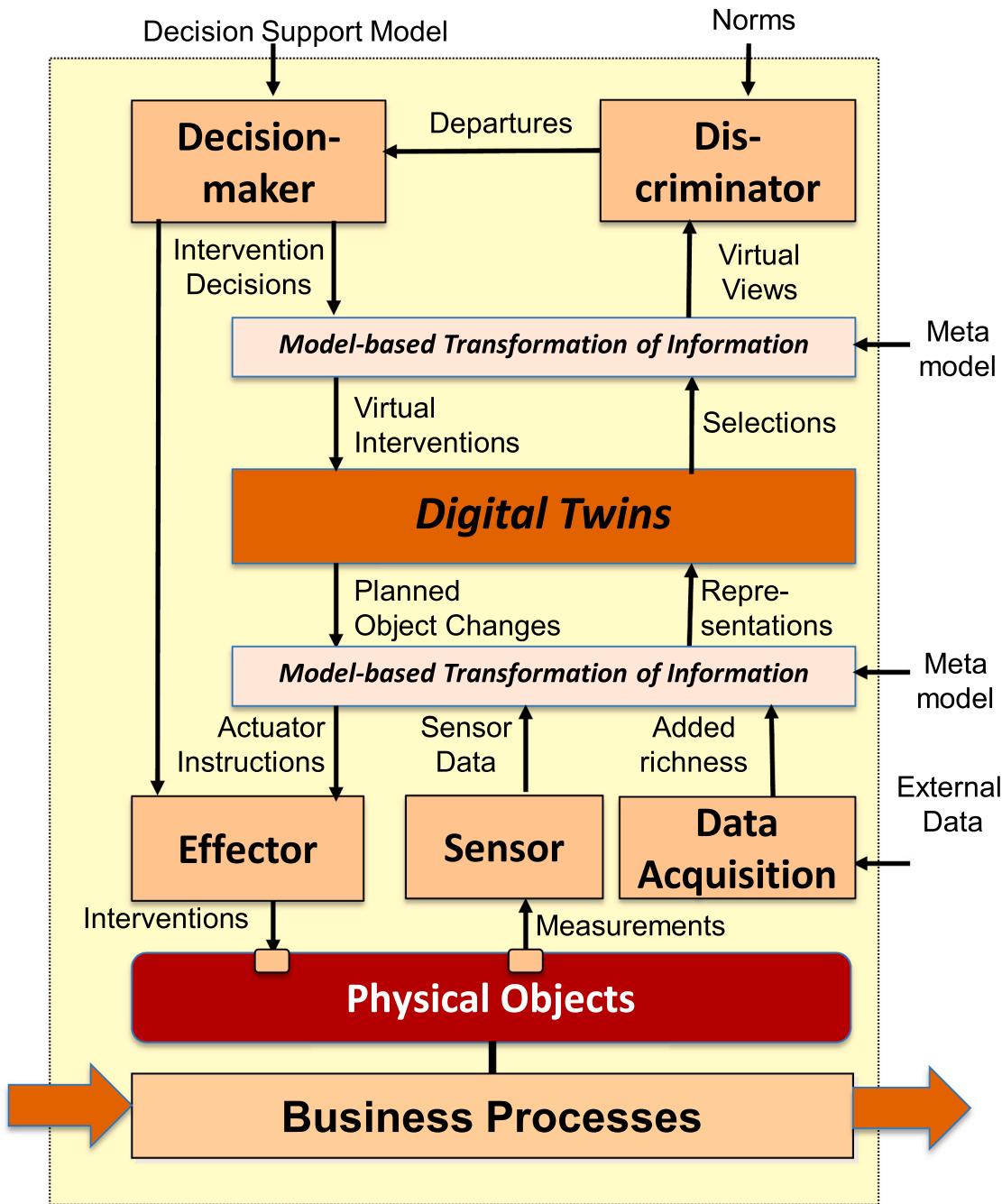


Fig. 6. Conceptual model for control based on Digital Twins, based on Verdouw et al. (2015).

discriminator, decision maker, and effector are present (de Leeuw, 1997; Int Veld, 2002). Fig. 5 depicts these control functions in a basic control model. The object system executes activities that transform input into the desired output. In farming systems these are the business processes of the involved actors that transform input material to final products at the end customer's location. The sensor function measures the actual performance of the object system. The discriminator function compares the measured performance with the norms that specify the desired performance (system objectives concerning e.g. quantity, quality and lead time aspects) and signals deviations to the decision-making function. Based on a control model of the object system, the decision-making function selects the appropriate intervention to remove the signalled disturbances. Finally, the effector implements the chosen intervention to correct the object system's performance.

#### 4.1.2. Farm control with Digital Twins

Digital Twins allow farmers to decouple the physical flows from information aspects of farm operations (Verdouw and Kruize, 2017). Decoupling of control means that the measurements of the object system's state are translated into a Digital Twin as visualized in Fig. 6. The control cycle starts with measuring the object system's state by the sensor function and with acquiring relevant external data (Verdouw et al., 2015). These data are then translated into a virtual representation of the controlled object system (model-based transformation) on the basis of a meta model. The Digital Twin includes all information relevant for the supported purposes of usage (i.e. control objectives) as specified in a meta model. Dependent on a specific purpose of usage, a virtual view may then filter irrelevant information and present it in such a way that it can be processed optimally by specific users (model-based

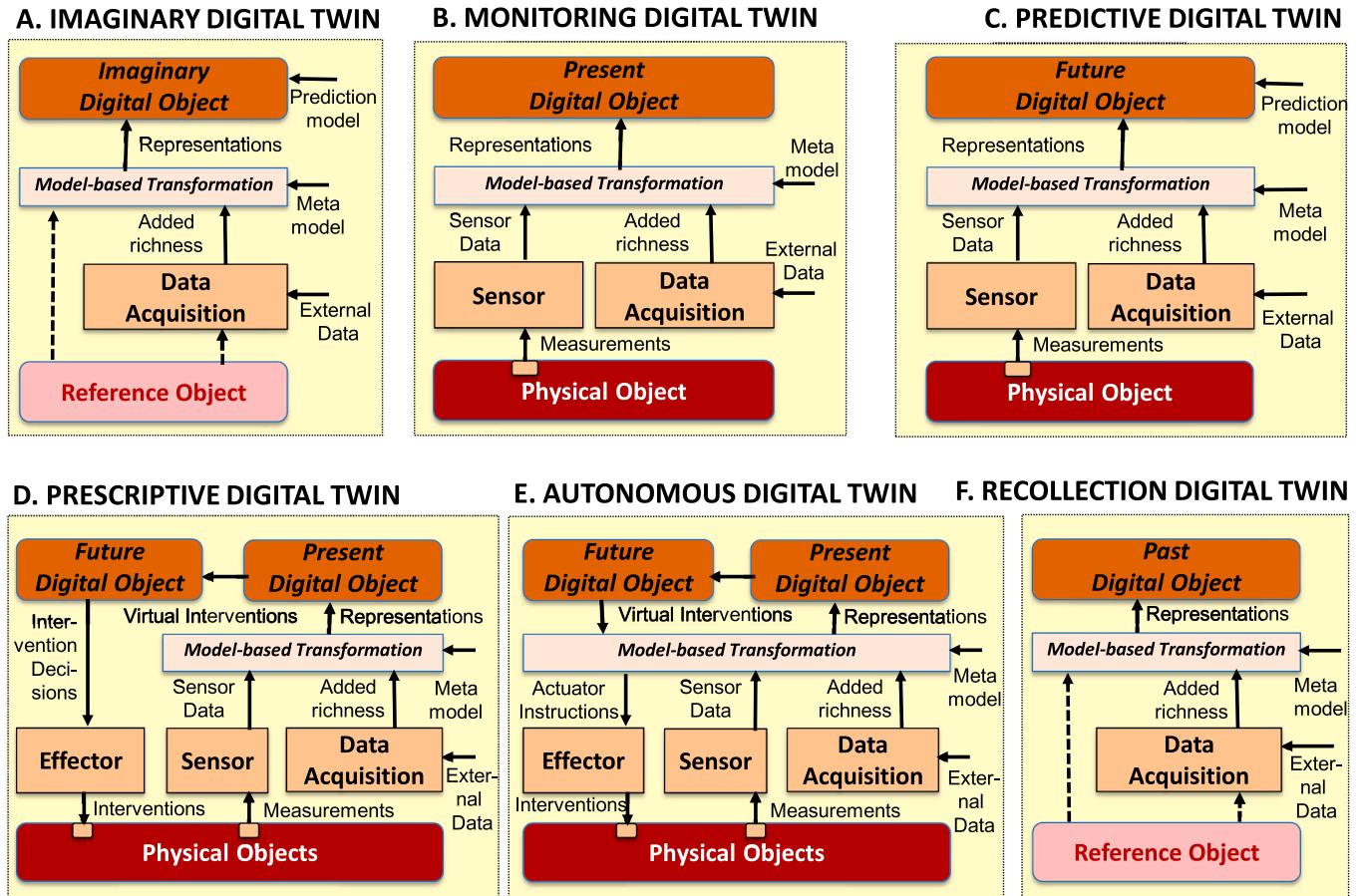


Fig. 7. Simplified Control Models of the Digital Twin Typology (excluding the Discriminator and Decision Making control functions).

transformation) on the basis of a meta model. The next control function is the decision-making function, which compares a virtual view on the object system with a specific control norm. Next, the decision-making function selects appropriate interventions for deviations based on its Decision Support Model, similarly as in conventional control systems. Lastly, the selected intervention is communicated with the effector function, either directly or via the Digital Twin using remote actuator systems.

#### 4.1.3. Impact Digital Twin typology on control model

The distinct categories of Digital Twins as introduced previously serve different control purposes. Fig. 7 provides a summarized overview of the main differences in the control model (adapted from (Verdouw et al., 2015)).

*Imaginary Digital Twins* represent the state and simulate the behaviour of reference objects that are not yet connected to objects that physically exist in the real-world. A reference object is a conceptual entity that specifies a typical object from the perspective of defining user requirements. Usually it is a combination of desired features that can be based on past experiences or they can be the result of a design process. It is also possible to select and depict a representative physical object (typical objects). Moreover, scenario data can be used to simulate the expected behaviour of reference objects based on prediction models.

*Monitoring Digital Twins* represent the current and historic state and behaviour of objects that exist physically in the real-world. The physical objects are equipped with tags for identification, usually barcodes or RFID transponders, and with sensors that measure dynamic properties of physical things. The virtual object uses these sensor data to generate a representation of the object based on a meta model, which might be implicit. Usually, the sensor data are combined with external data to

enrich the virtual representation.

*Predictive Digital Twins* project the future state and behaviour of real-life physical objects. The future states are forecasted by using a prediction model and subsequently a future projection of its behaviour is generated in conformance to a meta model. The prediction model uses information of the current and historic state of the objects, measured by sensors and AutoID devices, usually in combination with external data, e.g. weather forecasts or congestion information.

*Prescriptive Digital Twins*: represent the effects of interventions in a present Digital Twin on a future Digital Twin. The interventions can either correct a current issue as identified by a monitoring twin (reactive) or an expected future issue as forecasted by a predictive twin (proactive). Simulation of interventions in prescriptive twins allow for precise and realistic evaluation of corrective and preventive measure before implementation. The decision still is taken by humans and also the intervention is done without using a Digital Twin.

*Autonomous Digital Twins*: go beyond prescriptive twins because also the decision and implementation is done autonomously via digital representations. Prescriptive twins identify control issues based on monitoring and predictive twins and decide on optimal interventions based on prescriptive twins. Subsequently the selected intervention is translated into actuator instructions, that are implemented remotely. As such, autonomous twins run the complete control loop without any human involvement, but based on decision support models and control norms of humans. Autonomous twins can also be self-learning, which means that decision algorithms are optimized based on the measured response of real objects on control measures.

*Recollection Digital Twins*: represent the past state and behaviour of objects that no longer exist in the real-world. Like imaginary twins they represent reference objects, i.e. conceptual entities, but the nature of the

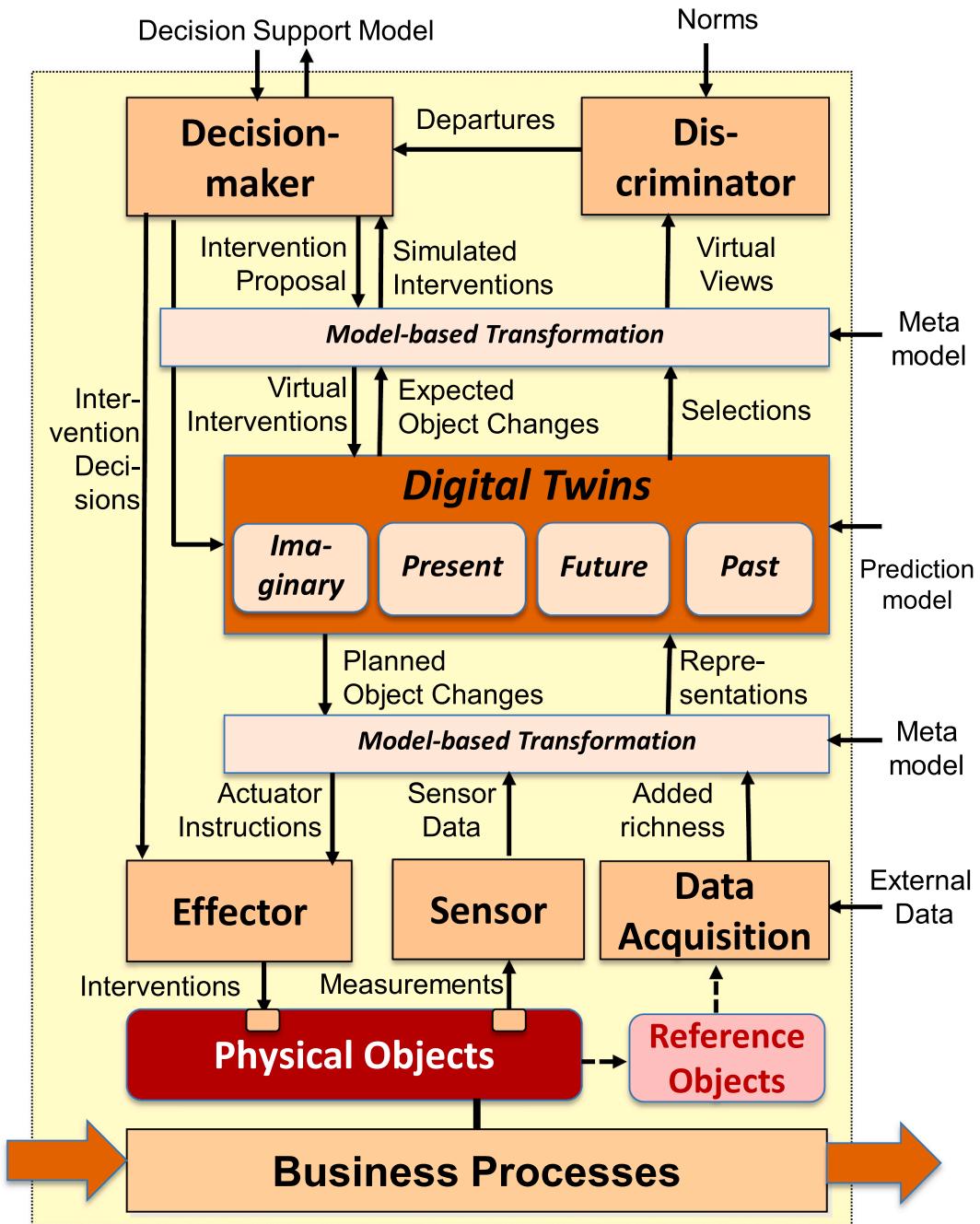


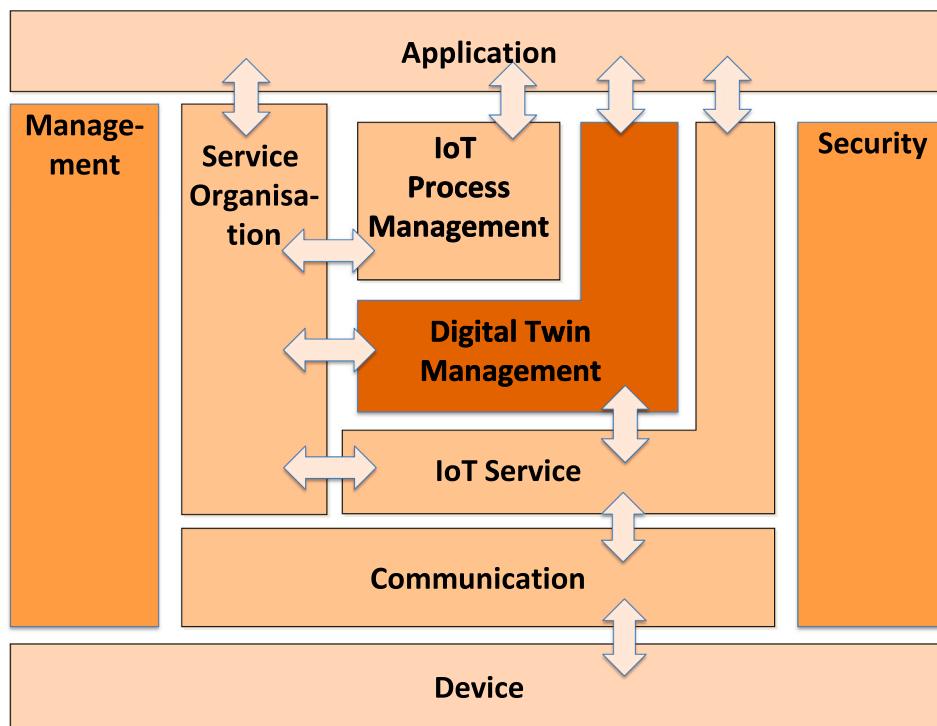
Fig. 8. Integrated control model for Digital Twins.

representation is completely different since there has been a connected real object in the past. Recollection twins have to depict this historical object in an accurate and reliable way, and as such they use all relevant data about this object.

#### 4.1.4. Integrated control model for Digital Twins

The previous sections have defined distinct control mechanisms of six Digital Twin categories. Fig. 8 incorporates these mechanisms into the control model. This model integrates all six Digital Twin defined categories, but not all elements will be relevant if less categories are applied. The integrated control model especially adds different types of the representation, i.e. imaginary, present, future and past digital objects. Imaginary digital objects represent reference objects that do not yet exist. Present digital objects represent the current state and behaviour of real-life, physical objects. Future digital objects project the

expected state and behaviour of objects. Past digital objects represent the historical state and behaviour of real-life objects or objects that no longer exist in the real-world. Furthermore a reference object is added to allow for the representation of conceptual entities that come into existence in the design phase of the product life cycle. Once the conceptual entity is materialized, the real object can be connected to the virtual object. This conceptual entity remains after the disposal of the real-life object at the end of the lifecycle. Reference object can also be relevant during the usage phase. An example is the usage of imaginary resources for planning purposes, which specify the type of resources and the properties necessary to do the job. Think of, for example, a virtual harvest machine having a certain capacity in specific weather and soil conditions. When the harvesting schedule becomes actual, a physical machine is chosen to do the job for the virtual one (having at least properties that match required ones).



**Fig. 9.** Implementation model for Digital Twins, adopted from IoT-A (Carrez et al., 2013), Virtual Entity is replaced by Digital Twin Management.

Finally, the interaction between the decision-maker function and the Digital Twins is elaborated. In prescriptive Digital Twins, intervention proposals based on decision support models are transformed into future Digital Twins. As such, the expected object changes of virtual interventions are simulated. The decision maker uses this simulated interventions to decide on the final intervention. Autonomous Digital Twins also translate this intervention decision into planned object changes and subsequently into actuator instructions. Autonomous twins remotely control the effector function that executes these instructions.

So far, the concept of Digital Twins and its underlying complexity were defined. The next section will present a technical model that is designed to implement this concept.

#### 4.2. Implementation model

This section proposes a technical model for the implementation of Digital Twins. A technical architecture describes the components of a system, interactions among components, and the interaction of a system as a whole with its environment (Trienekens et al., 2014). It is usually not drawn in one diagram but separated in multiple so-called architecture views each of which describes an architecture according to specific stakeholders' concerns (Clements et al., 2010).

For the purpose of this paper, we focus on visualizing main functionalities that are needed to implement the control model as developed in the previous section. Several technical architectures for Digital Twins are introduced recently. Schleich et al. (2017) proposed an abstract reference architecture that addresses some basic modelling principles for 'twinning' between the physical and virtual world properties, such as model scalability, interoperability, expansibility, and fidelity. Alam and Saddik (2017) developed a specific a Digital Twin architecture, that analytically describes key properties of cloud-based cyber-physical systems. Redelinghuys et al. (2019) designed an architecture for Digital Twins of manufacturing cells comprising six layers, including local data, gateways, cloud-based databases and a layer for emulations and simulations.

These authors consider Digital Twins as a next step in IoT-based

cyber-physical systems. As a consequence the proposed architectures are similar to reference architectures developed in the IoT domain, in which virtual representation of objects have an important role. Important IoT reference architectures include IoT-A, ITU-T and AIOTI (Verdouw et al., 2019). The Internet of Things—Architecture (IoT-A) provides a very in-depth definition of IoT's information technology aspects (Carrez et al., 2013; Gubbi et al., 2013). The International Telecoms Unions (ITU) has developed an IoT Reference Model which provides a high level capability view of an IoT infrastructure (ITU-T, 2016). The Alliance for IoT Innovation has defined a High Level IoT Architecture to achieve IoT semantic interoperability (AIOTI, 2018). In the present paper we adopted the IoT-A reference architecture because it most explicitly addresses virtual entities as a core element of the architecture. The remainder of this section will introduce the IOT-A reference architecture and how it supports the implementation of Digital Twins.

##### 4.2.1. The IoT-A reference model

The Architectural Reference Model for the Internet of Things is developed by the European project IoT-A (Gubbi et al., 2013). Besides establishing a common understanding of the IoT domain, IoT-A aimed to provide essential building blocks and design choices for developing interoperable IoT system architectures. The reference model includes five different sub models: an IoT domain model, IoT information model, IoT functional model, IoT communication model and an IoT trust, security and privacy model (Bauer et al., 2013; Carrez et al., 2013).

The ontological foundation is formed by the IoT Domain Model, which defines main concepts of the Internet of Things like Devices, IoT Services and Virtual Entities (VE), and how these concepts are related. Building upon these concepts, the IoT information model defines the structure (e.g. relations, attributes) of IoT related information in an IoT system on an abstract level. The Functional Model decomposes the main functionalities of IoT-based systems into groups in a layered view. The IoT Communication Model elaborates the technical communication for connecting the different elements of an IoT-based system, including a reference set of communication rules to build interoperable stacks. The

**Table 4**

Control model overview of the investigated cases.

Case	Within-field management zoning	Happy cow	Chain-integrated greenhouse production	Added value weeding data	Pig farm management
Main objects	Potato Crops, Field, Harvested Potatoes	Cow, Herd, Field	Tomato Crop, Greenhouse, Harvested Tomatoes, Truck	Weeds, Lettuce Crops, Field, Weeding Machine, Harvested Lettuce	Pig, Farm, Slaughterhouse
Time dimension	Present, Future	Present, Future	Present, Future	Present, Future, Past	Present, Future
Main farm processes	Grow and Harvest Potatoes	Produce Milk	Grow, Harvest and Distribute Tomatoes	Grow and Harvest Lettuce	Fatten and Slaughter Pigs
Digital Twin types	Monitoring, Predictive, Prescriptive	Monitoring, Predictive	Monitoring, Predictive, Prescriptive	Monitoring, Predictive, Prescriptive, Recollection	Monitoring, Predictive

sub models are elaborated in very detailed architectural views and accompanied by guidelines.

It can be concluded that the IoT-A is a very in-depth and rigorous reference model. It is beyond the scope of this paper to describe it into detail, but we focus on its IoT functional model (Fig. 9). For more details and the further technical implementation we refer to Bauer et al. (2013) and Carrez et al. (2013).

#### 4.2.2. Digital Twin implementation model

Basically, a Digital Twin architecture is composed of a physical object in real space, a digital representation of this object in the virtual space and the connection between the virtual and real space for transferring data and information (Grieves and Vickers, 2017; Redelinghuys et al., 2019). As argued previously, IoT technologies enable this synchronization of the physical and virtual worlds. The implementation model of our conceptual framework, based on the IoT-A functional model, addresses eight layers (Fig. 9). These layers range from a device

layer, which is attached to physical objects, to an application layer, which includes interaction with Digital Twin Users (based on Atzori et al., 2010; Bauer et al., 2013; Carrez et al., 2013; and Verdouw et al., 2016a).

The *Device layer* provides the hardware components that are attached to and directly interact with physical objects such as tags for unique identification, sensors and actuators. Important identification technologies used in agriculture include (multi-dimensional) barcodes and RFID tags (Verdouw et al., 2016a). Furthermore, a multitude of different sensors is used to measure dynamic properties of physical things including temperature, crop size, humidity, light, moisture, CO<sub>2</sub>, ammonia and pH values. Object sensing is also supported by mobile devices such as barcode/RFID readers and smartphones, which enable farmers to perform additional actions such as visual quality inspections. Furthermore, this layer includes remote sensing by satellites, aerial vehicles, and ground based platforms. Small unmanned aerial systems (i.e. drones) are increasingly used to realize a high spatial and temporal

**Table 5**

Implementation model overview of the investigated cases.

Case	Within-field management zoning	Happy Cow	Chain-integrated greenhouse production	Added value weeding data	Pig farm management
Device layer	Soil, crop and weather sensors, GPS tracker, actuators	Accelerometer sensor (neck mounted behaviour sensor)	Crop, Climate and Irrigation Sensors, Ventilation, Climate, Lighting and Fertigation Actuators	Weeder Sensors, Weeder Actuators, Weeder Terminal, Tractor Terminal GPS, Weather Station, Harvester Terminal	RFID tags and readers, water consumption, feed sensors consumption sensors, barn climate sensors
Communication layer	ISOBUS Channel, LoRa Network	Custom Farm LAN, Base Stations, Field Access Points	Wifi, GPRS/3G/4G Cellular, ethernet, Serial Bus	Farm WLAN, Farm LAN, CANbus	WIFI, GPRS, XMPP
IoT service layer	ISOBUS Task Controller, ISOBUS	VPN Concentrator	Fog Computing Services, FIWARE IoT	FireWire, SSD	IoT Adapters, local IoT middleware
IoT Process management layer	Modelling Services	n/a	n/a	n/a	n/a
Service organisation	Service Composition, Orchestration and Choreography	Service Composition, Orchestration and Choreography	Service Composition, Orchestration and Choreography	Service Composition, Orchestration and Choreography	Service Composition, Orchestration and Choreography
Digital Twin management layer	Soil Map Service, Variable Rate Application Map, FIWARE Orion Context Broker	Fertility Prediction Service	Climate and Irrigation Setpoints Estimation Service, Diseases and Condensation	Crop Growth Service, Yield Prediction Service, Machine Setup and Maintenance Service, Data Storage and Processing	Fusion Engine Service, Cloud Data Storage
Security layer	Identity Management, Authorization, Authentication, Network Security	Identity Management, Authorization, Authentication, Network Security	Identity Management, Authorization, Authentication, Network Security	Identity Management, Authorization, Authentication, Network Security	Identity Management, Authorization, Authentication, Network Security
Management layer	Configuration, Fault, Reporting, Member, State	Configuration, Fault, Reporting, Member, State	Configuration, Fault, Reporting, Member, State	Configuration, Fault, Reporting, Member, State	Configuration, Fault, Reporting, Member, State
Application layer	Akkerweb/FarmMaps, 365FarmNet, Configurable Dashboard,	IDA App, several FMIS's	Greenhouse Management Dashboard	Farmer Tractor Application, Steketee Dashboard, Akkerweb/FarmMaps, 365 FarmNet, AgLeader SMS Basic	IoT Dashboard, Business Intelligence Dashboard

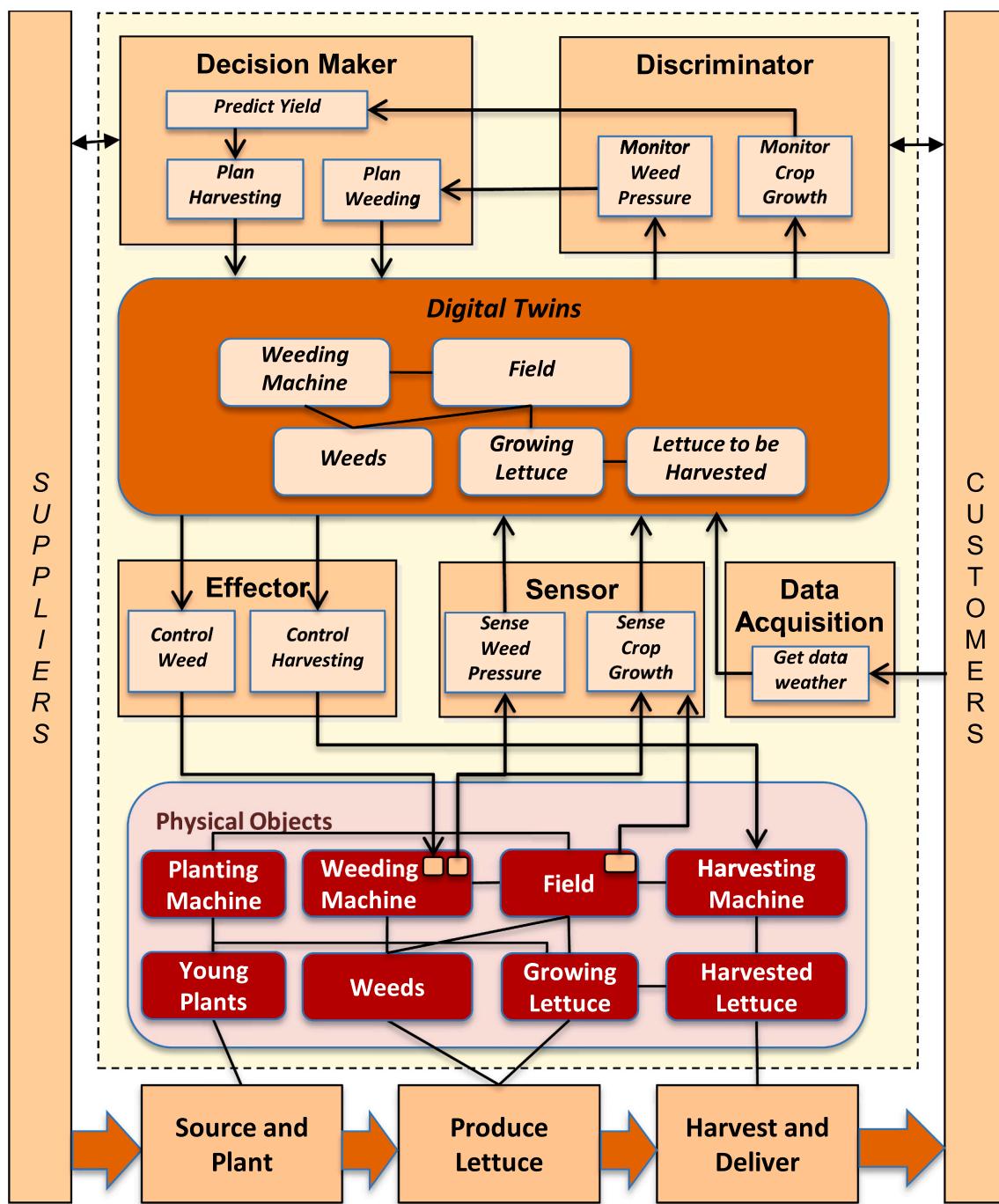


Fig. 10. Simplified control model of the weeding use case.

resolution and a high flexibility in image acquisition. Finally, in the device layer actuators are used to remotely operate objects such as tractor implements, climate control, irrigation, coolers, and lights.

The *Communication layer* manages the interactions between different components and enables the communication from the devices to the IoT services. It provides capabilities for networking, connectivity and data transport and enables end-to-end communication that crosses different networking environments.

The *IoT Service layer* contains services and functionalities for discovery, look-up and name resolution of IoT Services. It can be used to get information retrieved from a sensor device or to deliver information to control actuator devices.

The *Digital Twin Management layer* contains functions for interacting

with the IoT System on basis of virtual entities. It can give access to all the information about the Digital Twin, from sensor devices, databases or applications. Furthermore, it contains all the functionality needed for managing associations with the physical objects and monitoring their validity.

The *IoT Process Management layer* provides an environment for the modelling and execution of IoT-aware processes. Deployment of process models to the execution environments is achieved by utilizing IoT Services that are orchestrated in the Service Organisation layer. This layer acts as a communication hub between several other layers by composing and orchestrating services of different levels of abstraction.

The *Security layer* is responsible for the security and privacy of the systems and its users. It includes components like authorization,

authentication and identity management.

The *Management layer* is focussed on the configuration of the system. It also reports faults and determines the overall state of the system.

Finally, the *Application layer* provides the intelligence for specific control tasks based on virtual objects. It includes capabilities for usage of Digital Twins across its lifecycle. The different categories of Digital Twins are enabled by diverse technologies, including simulation and optimization tools, statistical forecasting, simulation and machine learning. This layer also includes the user interface for interacting with Digital Twins. The types of user interfaces can vary from 2D graphical user interfaces, as commonly used in personal computers, smartphones and tablets, to advanced 3D interfaces for Virtual and Augmented Reality glasses.

The remainder of this paper will illustrate the application of Digital Twins in agriculture by some cases of the IoF2020 project.

## 5. Application of Digital Twins in smart farming

### 5.1. Illustrative cases from IoF2020

The framework as presented in the previous sections is applied to five smart farming use cases of the IoF2020 project (Table 1). It is beyond the scope of this paper to exhaustively deal with the applied models for all cases. Therefore, we provide in Table 4 an overview of the applied control models and in Table 5 the applied implementation models. The models of the use case ‘Added value weeding data’ are described in more details as an illustrative example.

Table 4 provides an overview of the applied control models. Point of departure in all use cases is a particular farm crop or animal, i.e. potato, tomato, lettuce, cow or pig. These objects are nested in high-level objects, such as fields, greenhouses and stables. The plant use cases all also predict the expected output of the farming process, i.e. potatoes, tomatoes or lettuce to be harvested. Two use cases also virtualize equipment used, i.e. a weeding machine or truck. All use cases analysed combine multiple types of Digital Twins, starting with monitoring the actual state of objects and then predicting future states e.g. expected yields or animal health. Most of the use cases also include intelligence to advise interventions. The crop farming use cases also process these advices into prescriptive Digital Twins, e.g. by defining task maps. Most use cases focus on the usage phase of a lifecycle and do not include imaginary or recollection Digital Twins. Only the use case ‘Added value weeding data’ applies a recollection Digital Twin for optimisation of machine settings based on historical data about machine behaviour. None of the use cases have implemented yet autonomous Digital Twins.

Table 5 lists the main technical components that are used to implement the layers of the Digital Twin technical architecture. It shows that in the Device Layer all use cases apply domain-specific sensors and three use cases also use specific actuators. Most technologies for technical communication are based on standardized protocols of both conventional technology such as wired networks and recent wireless IoT networks such as LoraNet. The use case ‘Happy cow’ has chosen to apply a custom-built network consisting of distributed access points that enable communication up to several kilometers. Also in the IoT Service layer a combination of technologies is used. Process-based orchestration of services is not yet addressed. Only the first use case ‘Within-field management zoning’ includes some Modelling Services. In the Digital Twin Management Layer all use cases provide services that combine and store data from diverse data sources and represent harmonized virtual entities. These services also include intelligence for simulation or decision support dependent on the supported control functions (see Table 4). In the application layer, all use cases provide dedicated dashboards for the interaction with users and three of the use cases also integrate with existing farm management systems (e.g. Akkerweb/FarmMaps, 365FarmNet, AgLeader). Finally, all use cases comprise some generic technical functions for the service organisation, security and management.

### 5.2. Overview of the use case ‘Added Value Weeding Data’

When growing organic vegetables, weeding is one of the most important and frequent activities to control both the quality of the field and its produce (Lockeretz, 2007). In recent years, automated intra-row weeding machines have entered the market, enhancing the weeding process significantly. The most advanced weeding machines use machine vision applications to distinguish crops from weeds. These camera data can not only be used for automated control of the weeding task, but also as a valuable information source for farm management. This use case uses these location-specific camera data of a weeding machine as a main data source to provide actual insights into the number of lettuce heads growing on the field, the plants’ growth status, weed prevalence and best harvesting moment. As such it creates Digital Twins of a field, plants and weeds to monitor crop growth and to predict the crop weight and size of lettuce.

### 5.3. Application of the control model

The applied control model of the use case ‘Added value weeding data’ is shown in Fig. 10. The main farming processes are sourcing and planting young lettuce plants, producing lettuce in the field, harvesting lettuce which is ready for consumption and delivering it to the market. The main physical objects involved are planting machines and young plants, fields containing weeds and growing lettuce, weeding machines, harvesting machines and harvested lettuces.

The Digital Twins of this use case are used for monitoring weed pressure and crop growth, controlling the weeds to be removed and predicting the optimal moment of harvesting. To do so, the sensor function uses processed camera images to calculate crop parameters such as size. Furthermore, crop growth sensing adds weather data and field properties, including temperature, relative humidity, wind speed and direction, solar radiation and soil moisture (3 levels). The data acquisition function also includes external weather data.

These data are then transformed into Digital Twins. The virtualisation in this use focusses on the field, which implies that the main Digital Twin is a high-precision and actual heat map of a field. A field map comprises weed density and the number and size of crops (present), and the expected final weight and crop size of the lettuce (future). Planting seedlings are excluded. The Digital Twins of the individual lettuce crops and weeds are used by farmers during the weeding activity and afterwards the calculated parameters of every plant in the field are also available remotely. Furthermore, Digital Twins of the weeding machine is used to optimize machine settings afterwards (past).

The discriminator function uses the Digital Twins of weeds and growing lettuces to monitor weed pressure and crop growth, i.e. crop size and crop distance. The decision maker function translates the weed pressure into a planning of the weeding activities. A lettuce growth model is used to predict the crop weight and size per field section. The user sets a target value for crop weight and then the optimal harvest moment is determined. Based on this information the optimal moment of harvesting is determined and the harvesting is planned. For lettuce, growers get paid by lettuce head in the right weight class.

Finally, the effector function executes the planned weeding task. The weeds are automatically removed, controlled by the actuators in the weeding machine that apply machine instructions based on Digital Twin of the weeds. Because of the high-precision weed density maps, fields can be weeded partially, only where needed. Also the planned harvesting activities are executed by harvesting machines but they do not use customised machine instructions.

The control cycle partly takes place on-site within the weeding machine. Camera data are directly processed into local Digital Twins that distinguish crops and weeds. These Digital Twins are then instantly translated to actuator instructions and the weeds are removed without human involvement. However, all other control activities are done remotely by farmers who interact with the Digital Twins via cloud-based

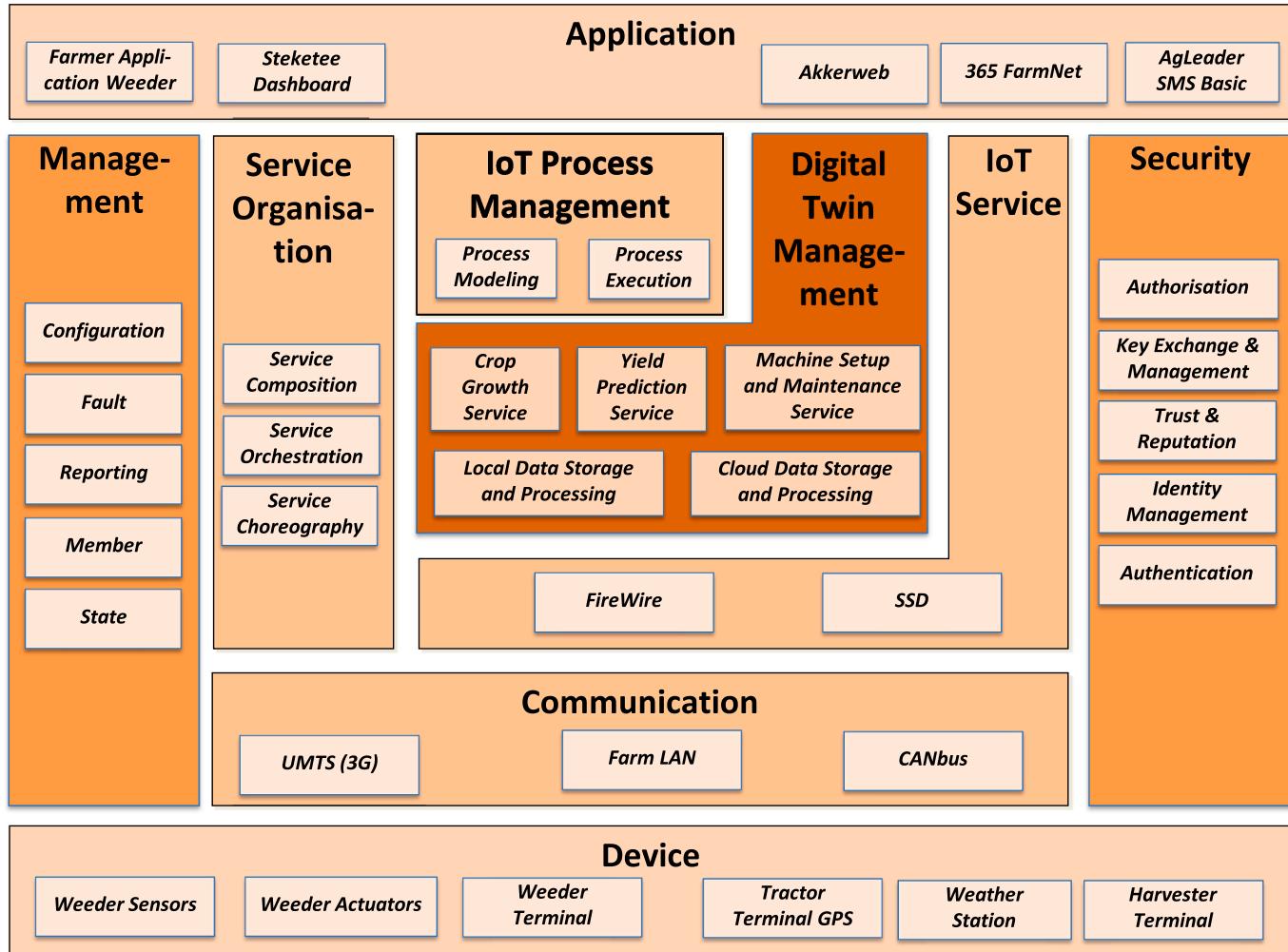


Fig. 11. Digital Twin implementation model of the use case 'Added Value Weeding Data'.

systems. The next section elaborates on how this is technically implemented.

#### 5.4. Application of the implementation model to the weeding data use case

The technical implementation of the use case is visualized in Fig. 11. The *Device layer* includes sensors (especially the camera's) and actuators that are embedded in the weeding machine, a weather station, and GPS connected to the tractor terminal. The data are directly processed and stored on the terminals on the weeder and harvester machine. The processed parameters such as GPS-coordinates, time stamp, crop size, distance, and weed pressure, are logged and uploaded to cloud databases after having weeded a field.

The *Communication layer* includes wired (CANBUS) interfaces and a wireless local farm network (LAN) for connecting the weeding machine, tractor and harvester and wireless network a for communication of machines and sensors with cloud systems (UMTS: 3G).

The *Digital Twin Management layer* combines, stores, processes and updates all data related to the Digital Twins of fields, weeds, growing lettuce, lettuce to be harvested, and weeding machines. It provides access to these twins for the farmer and machine vendor applications. The data storage and processing of the weeds and crops is done locally on the weeding machine. This layer also includes services needed to determine crop growth, to predict expected yield and to define optimal machine settings.

The *Application layer* allows users to interact with Digital Twins. Via

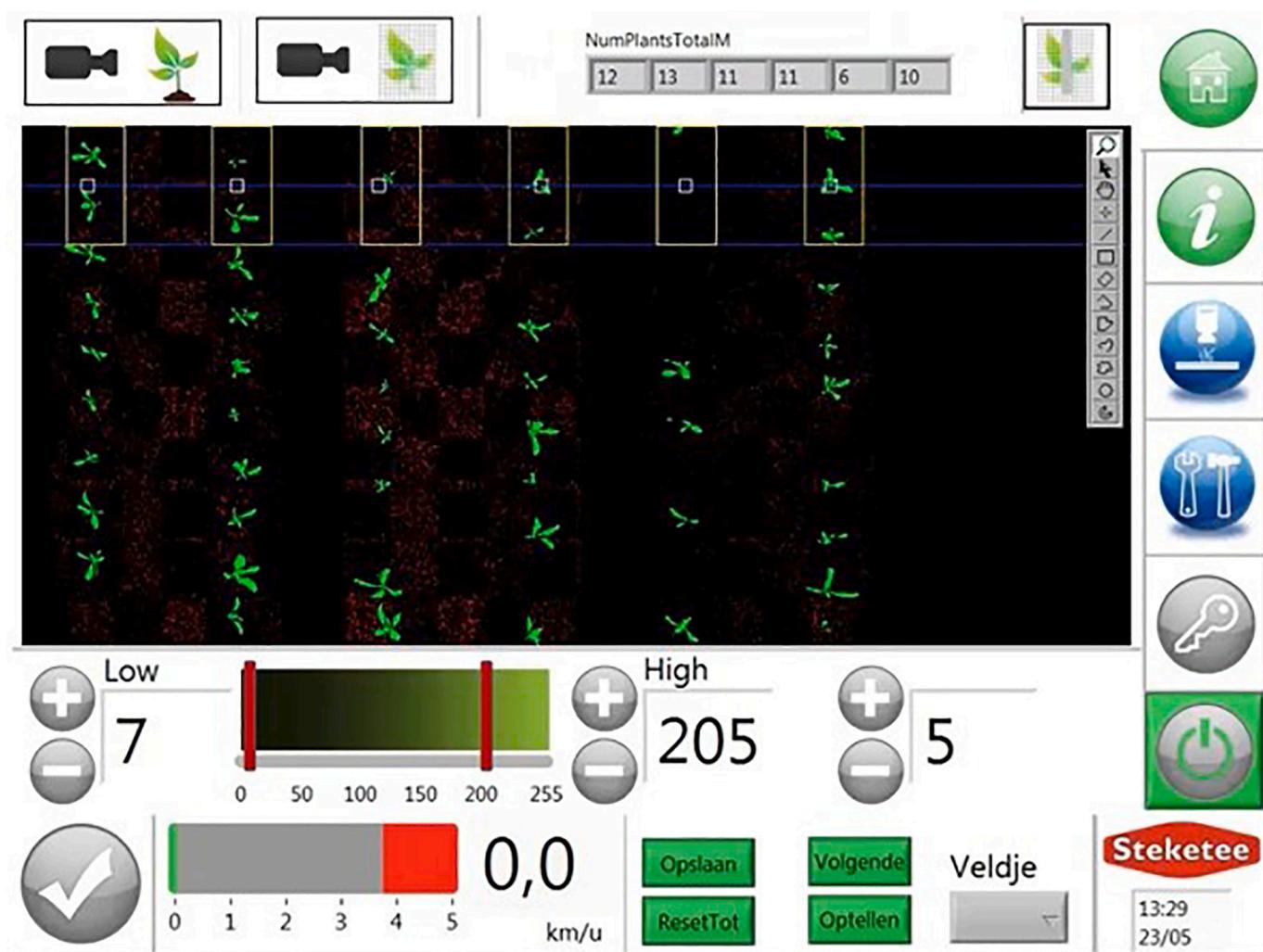
the weeder user terminal, farmers can monitor weeds and growing lettuce in real-time and intervene if necessary (Fig. 12). Via cloud dashboards, farmers can monitor weed pressure, crop growth and expected yield on field level. For this purpose the use cases integrates with existing solutions for geo information and farm management. Fig. 13 shows a crop growth example of the Akkerweb dashboard and Fig. 14 shows a weed pressure example in 365FarmNet. Furthermore, a machine vendor's dashboard can be used to configure and optimize machine settings. This is of crucial importance among others to correctly distinguish crops and weeds for different crop growth phases and light circumstances.

The other layers comprise generic technical functions that are similar to other use cases and that are already introduced previously (in Section 5.1).

## 6. Discussion and conclusions

### 6.1. Discussion

Digital Twins can be seen as a new phase in smart farming. Using Digital Twins as central means for farm management enables the decoupling of physical flows from its planning and control. As a consequence, farmers can manage operations remotely based on (near) real-time digital information instead of having to rely on direct observation and manual tasks on-site. This allows them to act immediately in case of (expected) deviations and to simulate the effect of interventions



**Fig. 12.** Digital Twins of the growing lettuce and weeds as a presentation in the user terminal of the weeder application.

based on real-life data.

The main contribution of the paper is that it has proposed a conceptual framework for designing and implementing Digital Twins for smart farming. The framework builds on an analysis of literature and a clarification of the concept of Digital Twins, which is still developing. An important novelty of the framework is that it adds a typology of Digital Twins based on the life cycle phases of the objects being virtualised. Depending on the perspective, the emphasis is currently often on monitoring or predictive Digital Twins. However, Digital Twins can already be created in the design phase of a life cycle and support the creation of its physical, real-life sibling. During operational usage, Digital Twins can not only be used to monitor and simulate the effects of interventions, but also to remotely control an object by using actuators. Finally, Digital Twins are also very valuable after disposal of a physical object e.g. for traceability, compliance and learning. So far, these distinct Digital Twin types are not explicitly addressed in the literature, which results in conceptual confusion. This paper has contributed to avoid this by introducing a typology and by defining the distinct control capabilities of each type in a control model.

The case studies show that there are already applications in the agricultural domain that are not framed as Digital Twins. This is not surprising, since Digital Twins are building upon existing technologies especially for precision farming, internet of things and simulation. However, especially more advanced applications, including e.g. predictive and prescriptive capabilities across the lifecycle, are still in an early stage of development. The designed framework was useful to

explicitly describe and analyze how Digital Twins are used in practice. As such, it has provided a new perspective on the cases that originally focused on the innovative application of Internet of Things technologies to farming. It also showed the value of not yet applied Digital Twin types, which inspired the use cases about potential redesign scenarios. For this reason, we expect that applying the Digital Twin concept, as described in our framework, can accelerate the development and adoption of Digital Twin solutions for smart farming. However, future research is needed to provide evidence for this hypothesis.

Furthermore, the implementation model of our framework only deals with implementing the enabling information technology. We did not take into account organisational and behavioural issues, such as the impact on supply chain collaboration, data ownership and governance, the potential emergence of disruptive business models based on Digital Twins, ethical considerations, and so forth. We would like to encourage researchers in these disciplines to also study Digital Twins, since these non-technical issues might be decisive for the success of Digital Twins.

Our intended follow-up work is related to the further development of the framework. In particular, we plan to elaborate the conceptual framework into an information architecture framework, which will comprise a consistent set of architectural viewpoints for modelling Digital Twin-based software systems (Tekinerdogan and Verdouw, 2020). This architectural framework will be the basis for developing Digital Twin applications that cover the entire life cycle.

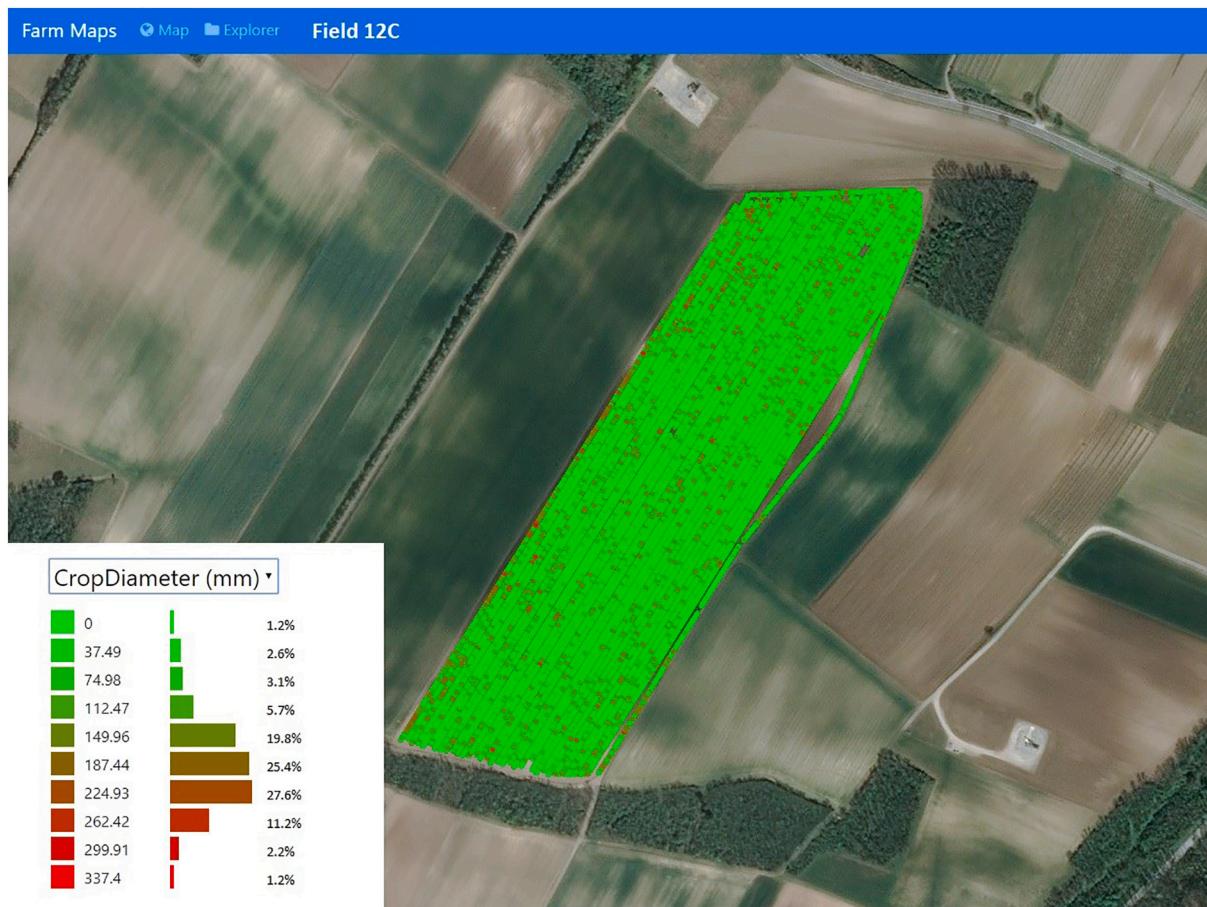


Fig. 13. Crop growth view on Field Digital Twin in Akkerweb a.k.a. FarmMaps.

## 6.2. Conclusions

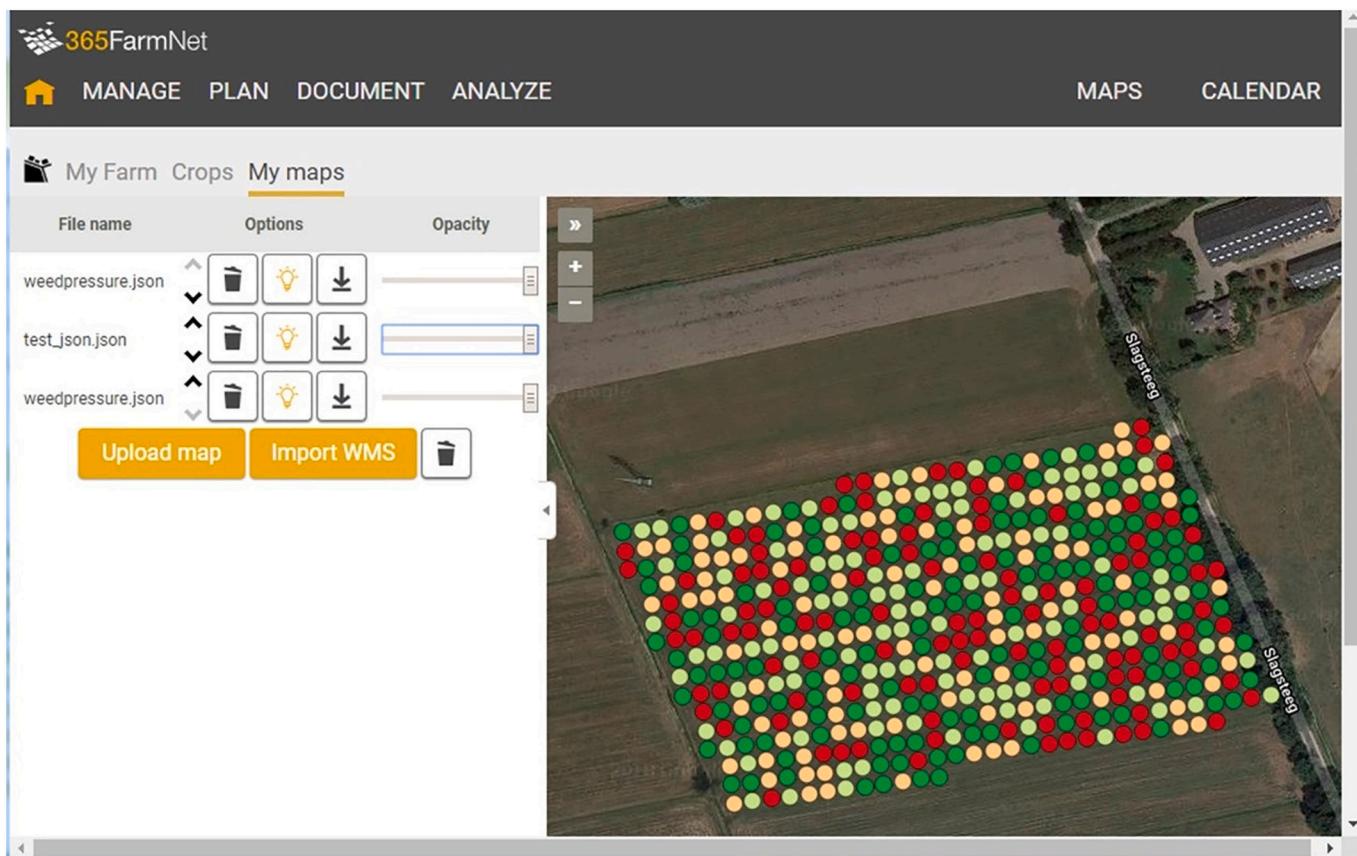
This paper has analysed how Digital Twins can advance smart farming. More specifically, it addressed the three objectives as mentioned in the introduction as follows.

Firstly, the paper has defined a Digital Twin as “a dynamic representation of a real-life object that mirrors its states and behaviour across its lifecycle and that can be used to monitor, analyze and simulate current and future states of and interventions on these objects, using data integration, artificial intelligence and machine learning.” Taking into account the role in the life cycle, six distinct Digital Twins are identified:

1. *Imaginary Digital Twins*: conceptual entities that depict and simulate reference objects that are not yet connected to objects that physically exist in the real-world;
2. *Monitoring Digital Twins*: digital representations of the (near) real-time state and behaviour of real-life physical objects, including its trajectory;
3. *Predictive Digital Twins*: digital projections of the future state and behaviour of physical objects using predictive analytics and based on (near) real-time data of the physical twins;
4. *Prescriptive Digital Twins*: smart digital objects that add intelligence for recommending corrective and preventive actions on the real-life objects;
5. *Autonomous Digital Twins*: operate autonomously and fully control the behaviour of real-life objects without on-site or remote intervention by humans;
6. *Recollection Digital Twins*: maintain the complete history of physical objects, which no longer exist in real-life.

Secondly, the paper has proposed a conceptual framework for designing and implementing Digital Twins in farm management. The framework comprises a control model based on a general systems approach and an implementation model for Digital Twin systems based on the Internet of Things—Architecture (IoT-A), a reference architecture for IoT systems. The control model defines the control functions and information flows among these functions for control systems based on Digital Twins. The implementation model classifies technical functionalities, from device layer until to application layer, needed to implement Digital Twin based systems.

Finally, the framework is applied to and validated in five smart farming use cases of the European IoF2020 project, focussing on arable farming, dairy farming, greenhouse horticulture, organic vegetable farming and livestock farming. The case-specific control models have provided concrete insights in how Digital Twins could enhance the smart farming systems of the use cases. Similarly, the case-specific implementation models have been useful to identify improvements of the technical architecture.



**Fig. 14.** Weed pressure view on Field Digital Twin in 365Farmnet.

#### Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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