Integration of Hypermedia-Agents, Microservices and Digital Twin for Smart Agriculture

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Abstract

Digital Twin (DT) has been one of the rapidly emerging technologies in the past few years. A digital twin is a digital representation of a physical asset reproducing its data model, behaviour, and communication with other physical assets. On the other hand, agents and multi-agent systems (MAS) are well established as a source of abstraction for intelligent engineering systems. Multi-Agent Microservices (MAMS) and Hypermedia MAS approaches are relatively new topics. This paper attempts to implement a Cognitive/ Intelligent DT for Smart agriculture based on a combination of Hypermedia MAS/ MAMS and semantic microservices. This work proposes a Digital Twin architecture and discusses realising this vision. A brief introduction of implementation is discussed in this paper. Moreover, it also concerns our future work on this.

Keywords

Digital Twin, Microservices, Hypermedia-Agents, Smart Agriculture,

1. Introduction

Arable Crop Farming is challenging. It covers a range of activities from tillage to harvest. Each activity comes with its own requirements and obstacles. Traditionally, farmers have responded to these challenges by adopting a conservative approach based on local knowledge of the farm built up over many generations. Much of that inter-generational knowledge aims to maximise the potential for making a profit. Changing their approach is a high-risk strategy as a mistake can result in a loss of income that can affect the profitability farm for many years to come, possibly to the point where the farm becomes no longer viable. Further, challenges such as population growth[1], global warming[2] and the energy crisis are combining to disrupt the fragile balance. For example, the increasing cost of Nitrogen has made current practices for its application becoming non-viable (loss-making) and is driving the adoption of practices that encourage more efficient use of Nitrogen [3].

Precision or Smart Agriculture (Farming) [4, 5] aims to help moderate these risks and address these challenges by offering farmers insights into the operation of their farms that help to increase confidence in understanding the impact of any changes they make. Precision farming helps to optimise production processes by monitoring and analysing environmental variables with the help of real-time data, and historical data [6]. The objective is to help farmers (or

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advisors, such as agronomists) make better decisions that will maximise return on investment. Such decision support services can also help farmers to adopt more sustainable practices or achieve key environmental goals (e.g. reductions in CO2 emissions).

In the last decade, Digital Twin (DT) technologies have emerged as an important approach in domains such as Smart Cities [7], Manufacturing [8], Healthcare [9], and Industry [10]. A DT can be defined as a digital representation of a physical living model that virtually describes a system and predicts the future based on real and historical data. To date, DTs have received less attention in Agriculture [11], where it is anticipated their application can achieve cost reductions, more detailed information, catastrophe prevention, positive economic impacts, decision-making aid, and more efficient management operations.

A number of key challenges exist when developing decision support services. The first is access to **high-quality accurate data**. Farmers are time poor, and naturally focus their activities on their crops rather than data collection or entry. Data entry is often delayed or forgotten and the accuracy can be low due to human error. To alleviate this data gap, decision support tools increasingly rely on a diverse range of data sources ranging from physical weather stations, sensor platforms and farm equipment to satellite and drone images. Some data sources are accessible locally others via the cloud. A second key challenge that emerges from this is **data integration**. Many of the data sources are provided through third party applications and there is little standardisation across data formats. Any integration strategy must not only support current data sources but also facilitate the integration of additional or alternative data sources as they emerge. A third challenge is **model generation**. Farming is a complex activity and there are a number of factors that affect the growth of crops. Even with accurate data sources, precise modelling of crop growth is challenging, and accurate long-term prediction is often considered a fools game. This paper seeks to address these challenges through the proposition of a novel architecture for Agricultural DTs that combines Hypermedia Agents, Microservices, and Linked-Data concepts.

2. Related Work

As described in [12], the term Digital Twin (DT) was first used by Grieves in 2003. First defined by NASA, various alternatives have been proposed [13, 14, 15]. This paper views a DT as a digital representation of a living thing that virtually describes a system and predicts the future based on real and historical data. There are four levels of a virtual representation such as Pre-Digital Twin, Digital Twin, Adaptive Digital Twin, and Intelligent Digital Twin [16] [17]. Pre-Digital Twin are created before the physical asset to support decisions on prototype designs to reduce any technical risk and resolve issues upfront using a generic system model. Level 2 DTs incorporate the physical asset data related to its performance, health, and maintenance. The virtual system model uses this data to assist high-level decision-making in the design and development of the asset, along with scheduling maintenance. The data transfer at this level is bidirectional. Adaptive DTs, provide an adaptive user interface that allow it to learn from the preferences and priorities of human operators using supervised machine learning. This DT makes real-time planning and decision-making during operations possible. Finally, Intelligent DTs supplement level 3 DTs to include unsupervised machine-learning capabilities, making it more autonomous than level 3. It can recognize patterns in the operational environment, and using that along with reinforced learning allows for more precise and efficient system analysis.

2.1. Digital Twin and Microservices

Microservices is an architectural style inspired by service-oriented computing [18]. Their benefits, which include maintainability, and scalability [19], make them useful tool for constructing Digital Twins. For example, [20] uses microservices implement a “Digital Twin-as-a-Service” (DTaaS) cloud model. In their approach, the DT is realised as a set of cloud services that store and analyse the data gathered from sensors, simulate the real-world objects, and support visualization. In another paper, the same authors explore the use of Apache Kafka as a middleware for their approach [21]. Microservices are used to implement a decentralised Digital Twin for network management and control in [22]. In [23], it is argued that semantic microservices are an appropriate strategy for delivering the functional and non-functional requirements of a DT service framework. Their approach combines microservices with Semantic Web technology and a workflow engine for service orchestration.

2.2. Digital Twin and Multi-Agent Systems

Multi-agent systems (MAS) are a style of intelligent distributed systems that are comprised of multiple interacting entities (agents) that work together to solve problems beyond their individual capabilities. The role of MAS in DT for Industry 4.0 is described in [24]. Conversely, [25] discusses their use for DTs of Smart Cities through the integration of an existing simulation model of Hamburg’s traffic system with the city’s real-time sensor network. From an agricultural perspective, [26] proposes the creation of DTs through the combination knowledge bases, multi-agent technology and machine learning methods. They follow this up in [27] by presenting a conceptual plant model based on ontologies and multi-agent technology for use within their DT. At a more conceptual level, [28] analyses the potential synergies between MAS and DT to support reasoning at both the individual and collective level.

2.3. Digital Twin in Smart Agriculture

The application of DT to agriculture has been the subject of a number of recent review papers [29, 30, 31]. A review of DT in agriculture for the years 2017-2020 is reported in [11]. Their review highlights that, while there are a few applications of DT in agriculture, most are at an early stage of design and do not offer the benefits other disciplines enjoy. The main exception was the work described in [32] which were part of a European Union-funded program. The authors believe there is still a long way to go before the agricultural community can fully seize the benefits of DT.

[33] conducts a systematic literature review of Digital Twins in agriculture, identifying current trends and open questions with the goal of increasing awareness and understanding of the Digital Twin and its possibilities. Again, the authors highlight the challenges of building DT for agriculture and identify key areas of future research, such as simulation, biological systems modelling and business model development.

2.4. Main Contribution

There is growing interest in the use of multi-agent systems for implementing Intelligent DTs. Microservices are seen as a valuable approach to delivering such systems as they facilitate their decomposition into a set of small services that can be more easily maintained and integrated.

Smart Agriculture has been shown to be a promising domain for the application of DTs to support the decision making of farmers and agronomists. However, it is also proving to be somewhat more challenging that other domains due to inherent complexities. As was discussed in the introductory section, any DT architecture for agriculture must support diverse data sources and facilitate both data integration and data modelling.

This paper seeks to address these challenges through the adoption of a Digital Twin architecture that combines microservices, multi-agents and linked data concepts to support the implementation of a Digital Twin for the Arable farming. Microservices are adopted to handle the complexity of the system in terms of the diverse data sources and the range of modelling services used to generate the virtual models. Linked data is proposed as an integration strategy for combining these microservices and providing a standardised data abstraction that can be used to access the underlying models and their outputs. Multi-agent systems are used to implement both decision support services and to perform internal house-keeping on the model.

3. Hypermedia-MAS Based Digital Twins for Smart Agriculture

This section introduces our approach to implementing Cognitive Digital Twins for Smart Agriculture. The approach combines a semantic microservice-based architecture [23] that exposes the data and services that underpin the DT together with a set of decision-making agents that provide the cognitive layer of the twin. These decision-making agents are modelled as a Hypermedia MAS [34] that is implemented using the Multi-Agent MicroServices (MAMS) architectural style [35].

3.1. Hypermedia MAS & MAMS

The idea of *Hypermedia MAS* was first proposed in [34] as an approach to building dynamic, open, and long-lived Multi-Agent Systems (MAS) [36] that are designed to inter-operate seamlessly with entities that are accessible through the World Wide Web. In [37], this vision is further enhanced with the view that agents should be woven into the hypermedia fabric of the Web. In this sense, the authors argue that the Web is a natural space for agents to inhabit as it provides a uniform interface through which they can interact with the external world, be it physical devices (sensors etc.) or digital services. In this vision, the Web acts as an abstraction of the external world that exposes artifacts and provides a way of mediating access to them.

In practice, this vision is realised through the adoption of the REpresentational State Transfer (REST) architectural style [38] which models each external artifact as a set of resources (or a single resource) that are identified by one or more Internationalised Resource Identifiers (IRIs) [1]. Interaction with a resource is achieved by combining the associated IRI and the HTTP protocol [2].

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[1] http://www.w3.org/TR/webarch/

[2] https://www.ietf.org/rfc/rfc2616.txt

For example, an HTTP GET request will normally return a representation of the current state of that resource in some agreed format. In a Hypermedia MAS, the agent must interpret this representation and decide how best to act, which typically involves the use of additional HTTP requests. The format used to represents resources is based on Linked Data [39], an approach to realising Tim Berners Lee's vision of the Semantic Web [40] through the creation of typed links that are embedded within documents that represent data from different Web sources. A key advantage of this approach is that Linked Data supports machine readability through the use of ontologies, encoded and interpreted using Semantic Web technologies [39]. An example of an early attempt to realise this vision is the Hypermedea platform [41].

The Multi-Agent MicroServices (MAMS) approach was introduced in [35] as a new architectural style for integrating Multi-Agent Systems into microservices architecture through the use of REST. In contrast with other approaches, MAMS adopts a view of agents as hypermedia entities that are not only able to interact with hypermedia resources using HTTP, but also have a hypermedia body that can be interacted with through REST. The existence of this body acts to immerse the agent within hypermedia space, giving it a tangible presence that allows plain old microservices to interact with MAMS agents without the need to use agent specific technologies or concepts. The body itself is modelled as a hierarchy of resources rooted at a resource representing the agent and referenced by an IRI. Querying the agents IRI returns a linked data representation that contains hyperlinks that can be used to navigate the agents body. For each resource in the body, there is a corresponding representation that combines the state of the resource together with any associated hypermedia controls.

One of the main benefits of MAMS is that it allows the seamless integration of agent technology with microservices-based systems. It is essential to understand that this integration is deeper than the kind of integration offered by other similar approaches. MAMS agents are not just situated in a hypermedia environment; and they are *immersed* in it. Agents not only control hypermedia resources, they are hypermedia resources. This allows plain-old microservices to interact with agent-oriented microservices in the same way that they would with any other microservice. Because of this, MAMS agents can be integrated into any microservice application. We can easily leverage the vibrant ecosystem of industry-standard tools and components and, where appropriate, adapt them for use with MAS.

From a Hypermedia MAS perspective, the ability of MAMS agents to interact with hypermedia resources makes it an ideal platform for realising the vision. Recent work enhances this further through the integration of Apache Jena[3] as a Knowledge Store and its application to two semantic web scenarios: collaborative route finding [42] and building management [43].

3.2. Proposed Architecture and Realising the Vision

In this section, we introduce an approach to implementing a Cognitive Digital Twin (DT) of fields used for Arable Farming (winter wheat in particular) that is based on a combination of the Hypermedia MAS/MAMS concepts discussed in section 3.1 and semantic microservices. Broadly, the approach highlighted in figure 1 is to implement a decentralised linked-data structure built from a suite of semantic microservices whose output is consumed by a Hypermedia MAS

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[3] http://jena.apache.org

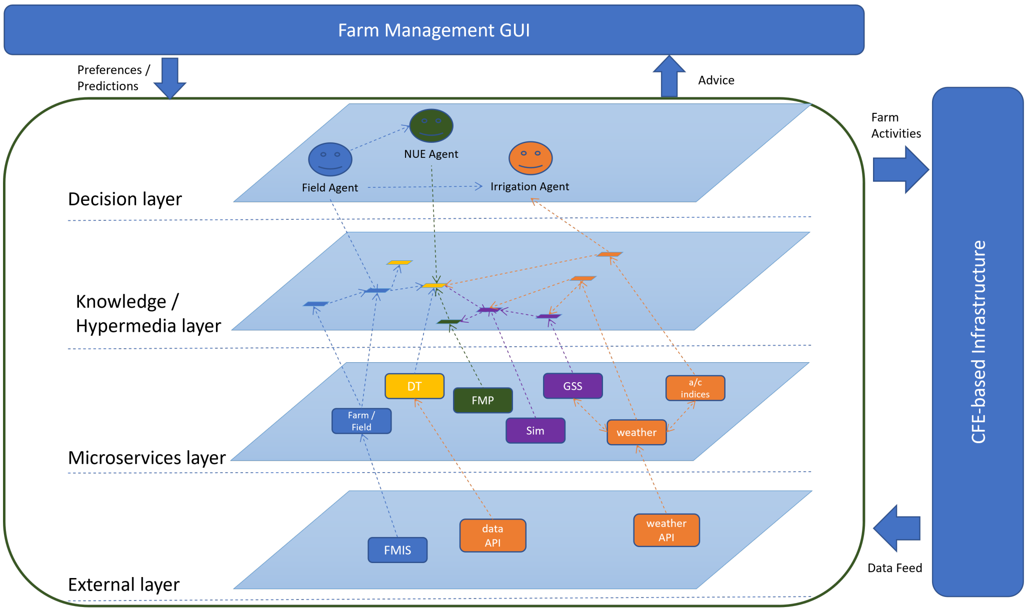

Figure 1: Digital Twin Architecture

implemented using the MAMS architectural style. Specifically, the aim is to create a suite of microservices that serve the various linked-data representations of the resources necessary to model the Physical Asset. These representations are underpinned by an agreed set of ontologies. The set of resources created is determined by one of the agents based on historical performance and the preferences of the farmer/agronomist. Jointly, the set of linked data resources used to implement the DT forms a knowledge graph that can be consumed directly by the Hypermedia agents. The knowledge graph evolves as the crop grows, and the expected yield becomes more precise during the growing season.

Conceptually, the architecture is organised over four distinct layers:

- **External layer:** This is the lowest layer of the architecture and it consists of a number of resources that will be used by the DT, including: data services, advisory services, prediction services. Examples of data services include Farm Management Information Systems (FMIS), historical weather services and cloud-based sensor data repositories (for accessing deployed IoT sensor data). Such services could be hosted as part of the farms digital platform or externally by third parties. Examples of advisory/prediction services include remote sensing services based on satellite data, decision support services, such as the UK's AHDB RB209 API[4] and yield, growth stage or weather prediction services.
- **Microservices layer:** This layer is responsible for abstracting external layer services into a standard format based on the agreed set of ontologies and providing additional internal data services that are specific to the DT. Examples of internal data services include a farm management plan service that captures crucial decision points for the coming season and services hosting real/simulated behaviour of the crop over the growing season.

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[4] https://rb209-api-v1.ahdb.org.uk/

- **Knowledge/Hypermedia layer:** This layer represents the set of resources created by the microservices available in the previous layer. The resources are all linked-data documents whose structure is underpinned by an agreed suite of ontologies. The decision about which microservices to use to create the resources is the responsibility of the Field agent that inhabits the upper Decision layer. Critical to this layer and the Decision agents is the use of linked data as it represents the data in a form that can be easily transformed into knowledge. The result is that this layer is basically a knowledge graph that spans the DT and provides an index to all the data contained within it.
- **Decision layer:** This final layer is responsible for handling all decision-making related to the DT. This covers the initialization of the twin and in-season recommendations/interventions as necessary. A library of agent designs is provided to support the different decision or monitoring activities that the DT can use. A Field Agent is created to oversee each DT. It uses the field management plan, the farmer's preferences, and the details of the crop being grown to oversee the season. The Field Agent's responsibility is to engage other agents specified in this layer to act as and when needed.

Constructing a DT based on the proposed architecture can be done incrementally with each increment involving a number of steps. The first step is to identify historical data sources and their associated APIs. These APIs form the first version of the External layer of the twin. The developer of the DT implements an set of microservices that extract required data from these external APIs and transform them into the internal linked-data representation. The internal microservices will be responsible for filtering and semantically enriching the raw data. They will also be responsible for managing the links between the different resources. For example, a farm resource should include hyperlinks to the associated field resources, and each field resource should link to the farm resource. One of the external data sources that is critical to the DT is the weather service. This service should provide both historical and current weather data for the field being twinned and should be implemented during the initial development cycle of the DT.

Once the initial set of external data sources has been integrated, the next phase is to generate a prediction for the upcoming season. To do this requires access to a growth stage model. Many models exist, but the most commonly used one is known as the Zadoks Growth Stage model [44], which defines a decimal scale that maps to the different growth stages of cereal crops. The transition between the growth stage is based on a series of thresholds for thermal time; an agro-climatic index derived from the sum of the average daily temperature (within given bounds) from the crop's date in the ground (Drilling date). Further details on this model can be found in the RB209 handbook[5].

Generally speaking, predicting crop growth is viewed as a fool's game as it is inherently linked to the weather, which cannot be predicted with a significant degree of success. In terms of the DT, we are not really trying to predict the upcoming season; instead, we are trying to identify various likely scenarios that could arise. The goal is to use those scenarios to help plan for the season. Because of this, our approach allows the farmer/agronomist to create a set of simulated seasons based on a range of weather scenarios that the farmer/agronomist identifies via the GUI. These scenarios are passed to the Field agent, who is responsible for

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[5] https://ahdb.org.uk/knowledge-library/the-growth-stages-of-cereals

managing all the DTs for a given field. The Field agent uses the weather service to create the specified scenarios and then uses the growth stage model to create the simulations. The agent then tasks a Planning Agent to generate an initial field plan based on the simulations created. The Planning agent uses knowledge of the crop type and the different simulations to identify windows in which different activities should be performed. This includes a window in which the crop can be planted (drilled).

Additional information can be incorporated into the DT. For example, the AHDB RB209 API can be used to generate recommendations for various nutrients based on the location of the field, the crop type, the expected annual rainfall and the underlying soil type. Knowledge of how to use underlying microservices to generate advice and predictions and how to access relevant data from the fields knowledge graph is encoded in the decision layer as part of the implementation of the different Decision agents. The DT can record the recommendations, and the amounts of each nutrient applied. For example, in the case of Nitrogen, it is common for farmers to apply the maximum possible Nitrogen to their fields each year based on stringent guidelines that government agencies enforce. Farmers do this because of the uncertainty around weather and the impact weather has on Nitrogen uptake. A particular issue arises in the week after the application of Nitrogen, where strong rainfall can result in up to 80% of the Nitrogen applied being washed away. On the other hand, over application of Nitrogen can lead to problems such as lodging where a plant grows too high, becomes top heavy and falls over.

Currently, a prototype of our architecture is under construction using data provided by our commercial partner[6]. At this point, we have developed microservices to access farm and field information. We also have a microservice that provides access to annual crop information for several historical years. From a weather perspective, we have integrated a weather service that combines historical and current weather information from multiple sources (both private and public) and which automatically generates agro-climatic indices such as the thermal days' index used in the growth stage estimation. Currently, the weather service is being used to generate a single weather timeline which is based on the average daily temperature for the five years preceding the harvest year. This weather timeline is used together with the growth stage service to create an initial simulation of the season. We have also implemented an internal service that wraps the AHDB RB209 API for nutrient recommendations. We are currently working on an initial prototype of the field management plan and an initial version of the GUI to allow us to explore the different resources created in the model.

In terms of agents, we have created an initialisation agent that traverses the farms and fields listed in the farm database and generates an initial DT for each year of data provided for each field. Currently, the data is represented informally as JSON rather than JSON-LD. We have chosen to adopt a ”schema last” approach to explore what the DT resources should look like before formalising those choices through adopting appropriate ontologies.

4. Discussion and Future Work

Our proposed approach is most similar to the approach described in [28]. In the work, the authors highlight the potential for a symbiotic relationship between agent technologies and DTs.

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[6] Unfortunately, source code cannot be released due to copyright

They argue that not only can agents use DT as a lens to understand the state of the underlying Physical Artifact but also that DTs can exploit agent technologies to deliver enhanced decision making, leading to the idea of Intelligent/Cognitive DTs presented in section 2.

We adopt a similar perspective, with the main difference being how we link the underlying digital twin with the agents. In [28], the agents access to the DT is mediated through an environmental artifact, a multi-agent construct that reflects current best practices in the MAS community. In this approach, the artifact acts as a conduit between the DT and the agent, constraining what information the agent is able to access and how it can affect the underlying DT. This has the effect of obscuring the details of the underlying DT and can potentially constrain its evolution. In our approach, the adoption of a Hypermedia MAS perspective (section 3.1) means that link between the agent and the DT is more open as it is modelled as a set of linked-data hypermedia resources that can be interacted with freely by the various decision agents. Further, through the adoption of a microservices approach together with established integration patterns, it is possible to design the microservices layer in a way that simplifies the integration of new components. A specific benefit of adopting a linked data approach is that the transition from one growth stage model to another is as simple as changing the IRI that a resource links to.

In future work, we are planning to focus on the following:

- **Identification of best set of the Ontologies to use:** Many ontologies available vary in complexity/scope. Choosing the correct set of ontologies is acknowledged as one of the most challenging tasks in developing linked-data systems.
- **Development of a library of internal microservices:** As experience with the architecture grows, it is expected that some standard microservices will emerge that are used across all DTs. These include internal microservices like the field management plan service as well as microservices that wrap external data sources.
- **DT Evolution and Update.** Revision of the microservices infrastructure to support the integration of new internal and external microservices over time through the adoption of industry standard service discovery platforms such as Netflix Eureka [7].
- **Introduction of new Decision Agents:** Over time, new decision services will be created or existing decision-making services will be improved. There is a need to be able to build a library of Decision Agents that encapsulate those new or improved decisions.
- **Transitioning to a Farm DT:** Modelling fields in isolation is not realistic. Practical Agricultural DTs will be realised as Webs of DTs [28] that aggregate field level DTs with other DTs of farm buildings, machinery or other critical infrastructure. The resulting farm DTs offer many opportunities for future research, for example, the creation of farm-level management plans generated through negotiation between self-interested Field Agents.

5. Conclusion

This paper has presented a novel architecture for Agricultural Digital Twins (DT) through the integration of Hypermedia MAS, Microservices and Linked Data technologies. While our work is at an early stage, we believe that we have developed the concept sufficiently to highlight

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[7] https://cloud.spring.io/spring-cloud-netflix/reference/html/

its potential. Specifically, we believe that this approach offers significant advantages in terms of the ability to adapt and evolve not only the decision-making services offered through the the DT over time, but also the decentralised data structure that underpins the DT through the addition of new modelling techniques or the extension of the model to additional data streams as they become available. A key enabler of this approach has been the adoption of the MAMS architectural style, which facilities the seamless integration of agents and microservices.

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