Evolution of Digital Twins

Subjects: Agriculture, Dairy & Animal Science
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A digital twin can be described as a digital replica of a real-world entity. It simulates the physical state and maybe the biological state and behavior of the real-world entity based on input data. It helps in predicting, optimizing, and improving decision making. It has revolutionized the industrial world, particularly the manufacturing industry, construction and healthcare sector, smart cities, and energy industry.

Keywords: Digital Twins

1. Introduction

Today, more than ever before, vast quantities of information are being captured, stored, processed, and used digitally. In 1990, before the first internet browser was released by Berners-Lee, less than 0.5% of the world's population was online. Over the last three decades, the internet exploded, and today, more than half of the world's population uses the internet [1].

Alternatively, computing power and storage technologies have also increased several folds over the last five decades. To put things into perspective, the latest smartphones that we use typically have 4 GB of RAM. When compared to the Apollo guidance computer [2] on Apollo T human-crewed spacecraft to land on the moon, this is more than one million times its RAM capacity [3]. This explosive growth in computing power, storage capacity and the internet has paved the way for numerous smart devices to exist today. The miniaturization of modern devices/technology has contributed to the advent of the smart devices. In 2020, it is estimated that almost 30 billion smart devices were connected via the internet [4]. This is almost a hundred-fold increase in smart devices since 2006. In other words, we now have almost 26 smart devices per person on this planet, on average.

It is estimated that we now generate about 2.5 quintillion bytes of data every day. Clearly, this volume of data is beyond human comprehension. However, newer advances in artificial intelligence (AI), big data and machine learning (ML) have the ability to process such a large volume of data and help us make sense of it (Figure 1). This has opened up new possibilities that never existed before. One such opportunity is digital twins.

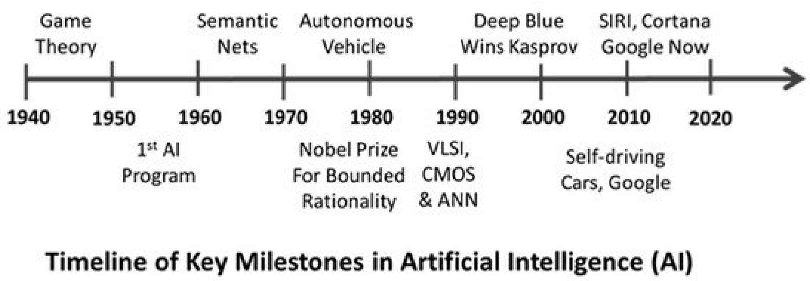

Figure 1. A timeline that shows key milestones in artificial intelligence. VLSI—Very Large-Scale Integration, CMOS—Complementary metal oxide semiconductor, ANN—Artificial Neural Network.

This review looks at the concept of digital twins from two perspectives. First, it looks at the origins and practical applications of digital twins that have been adopted across industries and sectors. Secondly, but more importantly, it looks at how digital twins technology can benefit livestock farming in the near future. Traditionally, livestock farming has been a highly experiential and manual industry. Experienced farmers use their knowledge or the knowledge of previous generations to run their operations and care for their livestock. Farming may be more imperfect and unpredictable than other industries, perhaps because it is exposed to the occurrence of weather shocks and pests and diseases. Digital twins promise to revolutionize potentially all aspects of livestock farming. By combining big data, real-time information from the individual farm, and AI, farmers can obtain a much more precise picture of what is occurring with their livestock, housing structures, and equipment. As such, digital twins technology promises to help farmers better predict and discourage negative animal behaviors, track and prevent diseases from spreading or becoming serious, and improve energy efficiency, as well as animal comfort and well-being in housing structures, and reduce the costs of livestock losses and breeding operations.

2. The Evolution of Digital Twins

At the simplest level, digital twins are realistic virtual representations of a physical entity (Figure 2). This physical entity can be anything from an automobile, windmill, or a manufacturing unit [5]. Sometimes it can even be something as complex as an entire city such as Singapore [6]. To better understand the concept behind digital twins, it is necessary to examine the origins of digital twins and how the concept has evolved to date.

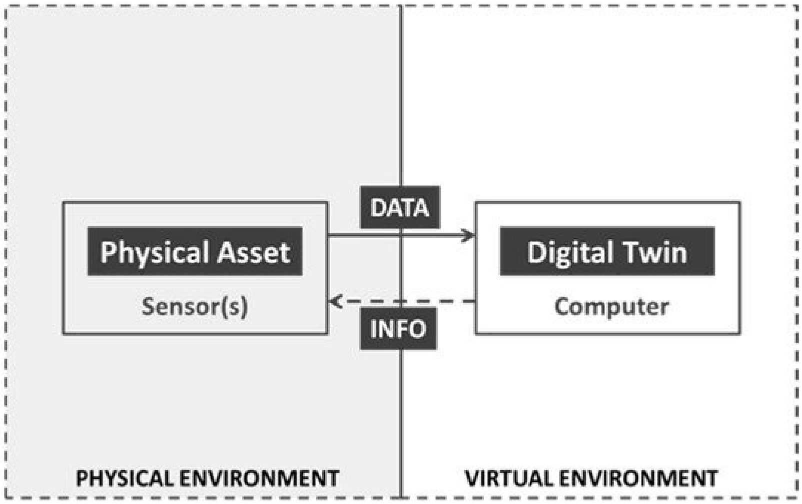

Figure 2. A conceptual representation of digital twin technology and its relation with a physical asset.

2.1. The First Digital Twin

As early as 1993, in his book *Mirror Worlds*, David Gelernter wrote about the possibility of software models that represent some chunk of reality [7]. However, even before that, NASA was one of the first organizations that used complex simulations of spacecrafts [8]. In 1970, the Apollo 13 mission had an unexpected explosion in its oxygen tank [9], which damaged their main engine and pushed the spacecraft away from its trajectory by about 400 miles a minute. To make things worse, the oxygen supply for the crew was slowly leaking into space. However, the mission team quickly modified several high-fidelity simulators to match the real-world conditions of the damaged spacecraft and used this to help the astronauts pick the right moves to land safely back on earth [10]. This was probably one of the first real-world applications of a digital twin.

However, it is important to note that digital twins were not a familiar concept back in 1970. Even so, this specific example met several key characteristics of a digital twin. For instance, the simulators sensed the real-world condition of the spacecraft and used that information to modify themselves. More importantly, it helped the team address what-if scenarios that were never considered in the design plan.

2.2. Lower Costs Mean Greater Benefits

Space crafts are extremely costly, mission-critical and inaccessible by anyone not on it. Therefore, in a sense, they were the perfect real-world applications for digital twins—because the high costs were well worth the potential benefits it could offer. At least this was true until a few decades ago. However, as discussed earlier, the cost of sensing, sending, storing, and processing real-world changes in physical entities has become exponentially lower. This opened newer opportunities for several other industries, including the biomedical and agricultural livestock sectors, to also benefit from digital twins.

2.3. Early Publications

John Vickers of NASA first coined the term “digital twin” in 2002 [11]. Around the same time, the research professor Dr Michael Grieves worked with Vickers to adapt the concept of digital twins as a way to improve product lifecycle management (PLM) in the manufacturing sector [12]. Initially, he called it the “Conceptual Ideal for PLM”. However, even during this early stage, he touched upon several key properties of digital twins [13]. In his paper, Grieves spoke about the difference between real and virtual spaces and highlighted the need for the exchange of data and information between the real and virtual entities to mirror each other.

2.4. The Following Years

Since 2003, interest in the concept of the digital twin has grown by leaps and bounds. Gartner now includes hyper-automation as the number one key strategic technology trend for 2020, and digital twins are a large part of hyper-automation [14]. Initiatives such as Digital Futures and the movement towards the Industry 4.0 paradigm are key factors in this growth of interest. In addition to this, several key advances across technologies, such as the Internet of Things (IoT), big data, and real-time sensors, have driven costs down.

Together, all this has allowed for several new applications of digital twins that were not possible earlier. A range of sensors can now collect data from a smart device and mirror that state in a digital twin in real-time [15]. In other words, we now have the technology to make a reasonably accurate digital twin copy that mimics the properties of real-world assets such as (but not limited to) its shape, status, and movement.

According to Gartner, approximately 75% of the organizations that were implementing IoT projects were already using digital twins [16]. Clearly, the concept is beginning to gain traction, at least among the early adopters. Recent research by Markets and Markets estimated the digital twins market at USD 3.8 billion in 2019. It also projected that this market would grow almost nine-fold to reach USD 35.8 billion in market value by 2025 [17].

2.5. Real World Digital Twin Examples

Today, digital twins are being used across sectors and industries in a number of ways, as shown in Table 1.

Table 1. A list of digital twin case studies across industries and sectors.

Industry	Sector	Digital Twin Types and Advantages	Reference
Boeing	**Aero Manufacturing**	**The digital twin asset development model has shown a 40% quality improvement in first-time parts/systems to deliver enhanced productivity gains.**	[18]
Halliburton	**Oil Field Service**	**Using different sensors to capture different dimensions of data while drilling oil wells. Uses this with virtual models to make drilling more efficient.**	[19]
Dassault	**Software**	**Using digital twins for various parts of the human body, thus, helping people benefit from less invasive and more personalized medical interventions.**	[20]
Unilever	**Fast Moving Consumer Goods**	**Creating virtual models of its factories to track and improve key factory performance parameters and production variables. Helped save USD 2.8 million.**	[21]
Royal Dutch Shell	**Oil and Gas**	**Using digital twins to design and recreate realistic real-time models of valuable assets. As a result, are able to reduce maintenance costs, as well as downtime.**	[21]
Bridgestone	**Tire Manufacturer**	**Experimenting with real-time data from tire sensors to improve precision safety systems.**	[21]

As one can see from all these examples, there are two common trends. First, digital twins are being applied by industry market leaders across sectors. Secondly, digital twins are being applied in areas that are mission-critical, because they have the potential to improve or transform their market position significantly. This is because digital twin technology is still its nascent stages. In other words, it has high learning, experimentation and implementation costs. These projects often cost millions of dollars per year.

Therefore, naturally, not many companies can afford such a significant investment into something that may not have immediate payoffs, unless of course, they are market leaders and are looking to further consolidate their leadership. In addition, this helps us to better appreciate their big bets. They want their huge investments to pay off with massive returns. This is probably why they are going for the big home runs with the digital twin technology. Does this mean that other smaller companies that cannot innovate with digital twins? What about sectors such as agriculture and livestock production that may not have large R&D budgets? To understand all this better, here is an analysis about what it means to implement digital twins.

3. Implementing Digital Twins

3.1. Key Properties

As discussed earlier, digital twins are virtual representations of a physical asset. Let us expand on this definition and look at some of the key properties needed to implement a digital twin.

First, to realistically represent a physical asset and mirror its behavior, the twin needs to obtain real-time feedback on how the physical or the biological asset is interacting with its environment, workload and other variables. This requires different sensors that can send and receive specific forms of data via the internet or some other privately secured network.

Second, we need the twin to be able to receive, store and process the large volumes of data in real-time. This requires a significant amount of computing, storage and data processing capacity. In other words, it has to make use of the latest advances in big data, data management and cloud servers.

Third, the twin must be able to make sense of the large volumes of continuously transmitted data. Since this is beyond the computing abilities of most humans, this invariably means using AI algorithms to discern between useful and non-useful information. It also means using AI algorithms to suggest recommendations and actions.

Fourth, the twin must be able to learn about different cause–effect scenarios over time and be able to apply the learnings to improve the performance of the physical asset. This involves running several alternate scenarios, test cases and what-if simulations. Again, this level of complexity is beyond human comprehension. This means that ML algorithms need to be trained under specific circumstances to learn, experiment and evolve the best possible course of action.

Finally, all this must be readily available to key human decision-makers via an interactive digital user interface. Typically, this will be some form of a display and processing unit such as computers, tablets or even smartphones (Figure 3).

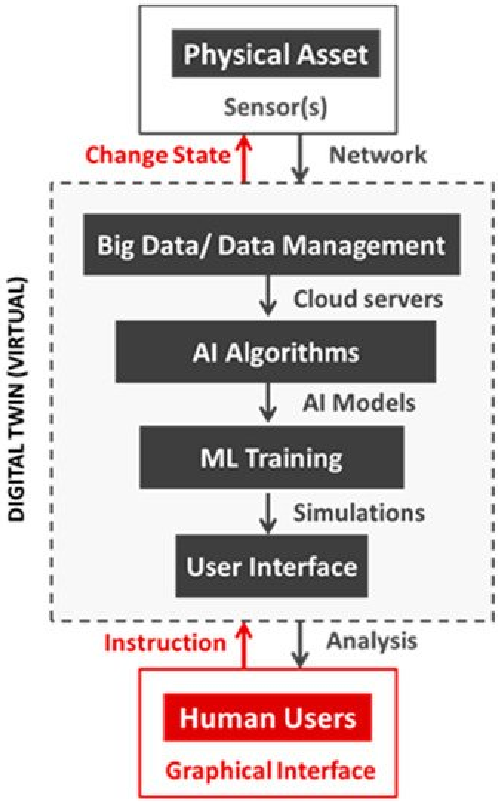

Figure 3. The flow of information between physical asset, digital twin and human users. ML: machine learning.

Key terms involved in the process of implementing digital twins are (1) the actual physical asset, (2) the virtual representation (digital twin), and (3) the human decision-makers.

In addition to this, there are several interconnections, information flows and states that can exist between these three entities. Most of them will vary from project to project, depending upon the scope of the digital twin. Broadly, any digital twin implementation is likely to have the terms described in Table 2.

Table 2. A summary of key terms used in implementing digital twins.

Key Terms	Description
Physical Environment	**Environment where the physical asset exists. Often not easily accessible.**
Virtual Simulation	**Environment where the virtual digital twin exists. Easily accessible.**
Sensory States	**Different possible states representing changes in the physical asset.**
Changes in State	**Switching between various states in the physical asset or digital twin.**
Twinning	**Synchronization of states between the physical asset and digital twin.**
Twinning Rate	**The rate at which this synchronization occurs. As close to real-time.**
System Processes	**Various processes that cause state changes to the asset or twin.**

3.2. Beyond Computer Models and Dealing with Uncertainty

Many industries already use computer models and simulations to reduce costs and improve efficiencies. In one sense, digital twins are also simulated computer models. However, there are several differences. The most significant difference is that computer models are built to explore or predict a wide range of cases. For example, we might have a computer model to determine the spread of coccidiosis among farm animals in a particular region. However, a digital twin, by definition, is a virtual representation of a single physical asset. In other words, a digital twin cannot help you make general predictions about a coccidiosis outbreak in a region. Instead, it can only help monitor the key health parameters of Stacy, the dairy cow in farm 1073 at Kentucky.

Thus, the scope of a digital twin is only one individual asset. However, because of this focus, a digital twin is able to go beyond the limitations of most computer models. Digital twins can mirror changes of the physical assets in real-time, with only minor delays ranging between a microsecond to a few minutes. Digital twins also collect and analyze substantially more data compared with most computer models. As a result, digital twins are also able to draw up more realistic what-if scenarios. Dr. Smith recently published an online resource that talked about these key differences (Table 3) [22].

Table 3. Dr. Matthew Smith’s INDRA Acronym.

A Digital Twin Needs to Be	
Individual	**It must represent a specific thing, e.g., “Daisy the cow” rather than a generic cow.**
Near real-time	**This also means that the digital twin should be “always on,” available for as long as its real-world counterpart exists.**
Data informed	**It must be updated via a digital measurement of the real-world thing, e.g., a soil moisture meter or a regular satellite observation.**
Realistic	**The twin must be a sufficiently realistic surrogate for the real-world thing.**
Actionable	**Information from the real-world twin must have the potential to lead to an action.**

Computer models are known to have gaps in understanding reality. However, a thorough understanding of the data behind them enables the creators to anticipate and correct erroneous results that manifest in the models. They can do so by using several error-correcting algorithms to reduce these errors that stem from the wrong assumptions about the environment. In contrast, a digital twin can potentially capture any data for which a sensor exists as the situation arises and therefore, greatly reduce the degrees of uncertainty.

In addition, unlike most generic computer models, the effective use of a digital twin does not entail an understanding of all the technical details behind its creation. Instead, users can focus all their efforts on learning about how the digital twin behaves under specific conditions. This is much like they would do with any asset in the real world, with almost instant feedback. This is an enormous advantage over generic computer models.

Several research and industry publications have already highlighted the benefits of using digital twins. Jones et al. (2020) performed a systematic literature review and mapped the perceived benefits of using digital twins against the respective publications that described it (Table 4) [23].

Table 4. Characterizing the digital twin: a systematic literature review [23].

Perceived Benefits of Digital Twins—From Characterizing the Digital Twin Research	
Reduces Costs	[24][25][26][27]
Reduces Risks	[27]
Reduces complexity	[28]
Improves after-sales service	[29][30]
Improves efficiency	[31]
Improves maintenance decisions	[32]
Improves security	[33]
Improves safety and reliability	[34]
Improves manufacturing processes	[35][36]
Enhances flexibility and competitiveness	[37]
Fosters innovation	[24]

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