Harnessing the Potential of Digital Twins: Lessons from Two Mature case studies

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Abstract

Many enterprises have not progressed their Digital Twin Projects to full scale. Daunting interrelated managerial challenges related to developing living learning models, introducing flexible processes, and scaling and integration impede progress. We describe the strategies that General Electrics and Philips are pursuing to address these challenges.

1. Introduction

Digital Twins (DTs) are living-learning models of assets, systems, and networks that integrate data from both the digital and physical world to enable the continuous monitoring of systems and machines and the provision of predictive and prescriptive outcomes. DTs vary in scale and complexity and have soared in popularity in recent years. As companies continue to invest in Internet of Things (IoT), it is expected that digital twin's adoption across industries will increase[1].

Early predecessors of the digital twin technology[2] date back to the 1960s in the context of space programming. Such early predecessors relied significantly on simulations operating in isolation from a physical asset which did not reflect its current configuration nor its evolving or future state. Fueled by recent technological advances in IoT, artificial intelligence (AI), cloud computing, and augmented digital reality, digital twins have become strategic tools with diverse applications. Although digital twins are still in the early stages the types of problems they can solve are far ranging, spanning many industries and contexts.

Our interviews with executives across industries reveal a diversity in both digital twin types-- digital twins of products (cars, planes and associated components), infrastructure (bridges, railways, or entire cities), supply chains, the human body-- as well as the type of problems that DTs can address. Specifically, our analyses reveal companies use digital twins across industries to pursue different objectives: to avoid catastrophic failures, improve professional and personal health, manage supply and demand, to enhance operational performance to personalize product and service offerings, and/or create novel innovation opportunities. Table 1 details the objectives companies pursue when deploying a digital twin, the type of problem the DT addresses, the solution enabled by the DT along with examples of twins in each category. Although, the level of DTs' maturity across applications and industries differs. For instance, DT technology is being used in healthcare to provide a visual representation or simulation of physical and biochemical factors of a person and how particular treatments, procedure planning, prevention of injury and other healthcare applications will benefit them. Similarly, the retail industry can use digital twins to simulate and represent psychographic and demographic information. They can also use it for client modelling and role-playing scenarios to train and better prepare their salesforces and other employees.

Despite the increasing popularity of DTs and the diversity of problems they can address, very few companies have succeeded in leveraging the full potential of this emerging technology. According to a recent survey only 13% of organizations have developed full-scaled digital twins. Digital twins combine multi-physics simulation, data analytics, machine learning and other related digital capabilities

[1]Estimates suggest that by 2022, there will be more than 25 billion connected sensors and endpoints,[1] and digital twins will exist for potentially billions of things (Gartner, 2000).

[2] The NASA applied the concept of "pairing technology" a predecessor of the digital twin technology since the beginning of space explorations to handle simulations of complex systems such as rockets and spaceships.

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to demonstrate the impact of various scenarios and environmental conditions, assess the current configuration of an asset and anticipate its future states. Although, many of the challenges related to data analytics are generally comparatively mature and well-understood [e.g., 1, 2], and some aspects of deploying AI and machine-learning models are similarly well-understood [4]. Integrating such capabilities for complex interdependent multi-component twins that continuously change, learn, and evolve give rise to unique challenges and emergent properties, that very few companies have succeeded in overcoming.

In this article, based on preliminary interviews with over 30 executives in firms across industries, in addition to two in depth cases with General Electrics (GE) and Philips, we introduce current and emerging uses of digital twins and detail the challenges faced and lessons learned in designing and deploying different digital twins from two mature cases.

2. Description of our Research

To illustrate the challenges and solutions used by organizations to manage DT in practice, we describe the experience of General Electric (GE) and Philips. We selected these cases because: (1) they have deployed complete DT solutions which cover the full DT spectrum (e.g., from design and production into actual use); (2) their DT's maturity is advanced; (3) Both cases combine real-time data collection from sensors with physics based and machine learning models; (4) the DT(s) operated are dynamically updated during the lifespan of the physical object or process.
In the following, we describe the challenges the team faced and the specific practices that the respective project teams employed to address the challenges faced.

3. Challenges

Our case discussions revealed that DT projects have three distinct challenges that set DT apart as a unique data phenomenon. These challenges, and the new requirements they bring, are detailed below.

Combining Physics, AI and simulation models

DTs rely on a combination of physics, AI and simulation models. Physics-based model require expert knowledge and advanced modelling techniques and are necessary to simulate different damage scenarios to be tracked during the operation of the digital twin. However, compared to data-driven models, physics-based models may be less accurate because they are sometimes over-simplified. To improve the accuracy of a physics-based model, usually it requires engineers to redevelop the model by comparing the prediction and measurement based on machine learning algorithms. Physical sensors are further attached to an object and can provide an accurate picture of the physical object as it operates and can sometimes be used to generate an inside picture of the inner workings of the physical object including temperature, corrosion, and start and stops. The resulting significant amount of data is employed to train the machine learning algorithms, that serve as a digital twin to detect damage, or to select an appropriate model, in the structural system.
In other words, the physics-based model amplifies the interpretability of machine learning tools. According to GE, CTO Colin Parris "*When you look at a wind turbine and try to see how to characterize the wind that's coming into that turbine, you quickly realize that wind speed changes based upon the height of the turbine, it is not a constant…It also changes at every hour of the day. That is such a complex thing it can't be modelled by a physical equation... So we use AI and neural nets to model that*".

However, when physical sensors are impossible to use to map the internal dynamics, it is necessary to rely on advanced mathematical or other simulation methods to ensure an accurate understanding of the phenomenon you are trying to model. Virtual sensors provide an alternative when a physical sensor cannot be placed in the preferred position due to spatial conditions (e.g., lack of space for a sensor), a hostile environment (e.g., exposure to acids or extreme temperatures) or existing regulations (e.g., in healthcare). According to Philips Ger Janssen, Head of DT department: " *For some systems, we could not add sensors but what we could do is add virtual sensors to the environment of the system… so in the same room or in the operating room and [We] take care to measure data that [We] can relate in one way or another to the performance of the system…that is how we tried to mitigate that challenge*." The precision of such virtual sensors is determined by comparing the data they generate to that of sensors on non-moving components.

Integrating DT subcomponents into a system

Although an increasing number of firms use a proof-of-concept strategy for digital twins' subcomponents, they often overlook the capabilities required to integrate and scale up. In doing so, they focus on single assets in isolation without developing an understanding of how such assets connect to up/downstream data and processes or how a component or an asset can integrate into a system. Yet integration, for example scaling from a component into an asset and then into an entire system remains one of the greatest challenges of DTs according to GE's JR: "*So you first do a DT for a pump and then you would build the DT of the motor that is driving that… There is a motor, there is a coupling and there is a pump in that system, attributes of the motor can impact the pump, likewise the pump can be impacted by something upstream where the pressures are different… So how do you bring all of that together is challenging and I think one of the greatest challenges of DT such that you can roll-up*."

Making a complete digital twin of an aircraft, a human body, or any complex system will require combining multiple submodels developed for a specific problem, obtained from multiple repositories. Invariably, the submodels will be encoded in different formats, use different units, be solved using different solvers, have their own operational envelope and have their own uncertainty tolerances. Integration of different subcomponents requires research to manage information flows between models, quantify uncertainty across coupled components and manage fidelity of an overall system simulation that involves multiple components across different temporal and special skills [3]. These are all essential components for achieving digital twins at scale.

Developing "living", changing twins where "fixed" software applications are the norm.

Unlike fixed software applications or static data models, digital twins are dynamic, "living" entities that evolve in real time. According to GE's Vinay Jammu, VP of Analytics and Digital: "*DT are changing models: the data changes, the physical twin gets inspected, cleaned, repaired, it gets new components (e.g., a new blade). So the data has to continuously change and the DT needs to evolve as the state of the physical twin evolves.*"

DTs learn, update, and communicate with their physical counterparts by exchanging data throughout the asset lifecycle. This synergistic two-way coupling between the physical system, the data collection and the model sits at the heart of complex adaptive systems paradigm [5]. Although several dynamic data-driven application methods have been developed and successfully deployed, when and how to perform these calibration steps within the context of the DT operation remain challenging [6]. At Philips, [*We] make sure our systems are connected so any change is communicated accordingly, we also ensure that any update is registered in a proper way so that my DT knows about it. Because otherwise, it does not make sense to have your DT as after a few rounds of maintenance, your DT is not accurate anymore, and that is of course the essence of the DT."* Ger Janssen. GE digital relies on four ways of learning to ensure its DTs evolves in real time. The first is *learning from self*, can the engine learn from itself and real data that comes back. The second is *learning from humans*, last time I made a mistake so decisions from the last time mistake, when somebody inspected the DT and got additional information or from monitoring similar assets. The third mean is *learning from simulations.* GE Digital learns from powerful simulators that track everything from potential human activity within the organization to various extreme scenarios involving its huge test sites and operations. Such diverse forms of learning are integrated to ensure the DT is a living, learning system.

4. Conclusion

Despite the promising DT forecasts and the increased use of digital twins across sectors, very few companies have realized the full potential of this emerging technology. In this article we discuss three challenges companies face when deploying DT and the strategies deployed by two mature cases: Philips and GE to address the challenges faced.

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