Simulation Foundations, Methods and Applications

Michael Grieves
Edward Y. Hua *Editors*

Digital Twins, Simulation, and the Metaverse

Driving Efficiency and Effectiveness in the Physical World through Simulation in the Virtual Worlds

Springer

Simulation Foundations, Methods and Applications

The modeling and simulation community extends over a range of diverse disciplines and this landscape continues to expand at an impressive rate. Over recent years, modeling and simulation has matured to become its own discipline, while continuing to provide support to other disciplines. As such, modeling and simulation provides the necessary conceptual insights as well as computational support which has an established record of significantly enhancing the understanding of dynamic system behavior and improving the system design process, as well as providing the foundations for computational sciences and practical applications, from cyber-physical systems to healthcare. Hybrid methods and combinations with artificial intelligence and machine learning open new possibilities as well. The ever-increasing availability of computational power and the availability of quantum computers make applications feasible that were previously beyond consideration. Simulation is pushing back the boundaries of what it can be applied to and what can be solved in practice. Its relevance and applicability are unconstrained by discipline boundaries.

Simulation Foundations, Methods and Applications hosts high-quality contributions that address the various facets of the modeling and simulation enterprise. These range from fundamental concepts that are strengthening the foundation of the discipline to the exploration of advances and emerging developments in the expanding landscape of application areas. The underlying intent is to facilitate and promote the sharing of creative ideas across discipline boundaries.

As every simulation is rooted in a model, which results from simplifying and abstracting the reference of interest to best answer research questions or support the application domain of interest, we understand the model development phase as a prerequisite for any simulation application. There is an expectation that modeling issues will be appropriately addressed in each presentation. Incorporation of case studies and simulation results will be strongly encouraged.

Titles of this series can span a variety of product types, including but not exclusively, textbooks, expository monographs, contributed volumes, research monographs, professional texts, guidebooks, and other references.

These books will appeal to senior undergraduate and graduate students, and researchers in any of a host of disciplines where modeling and simulation has become (or is becoming) an important problem-solving tool. Some titles will also directly appeal to modeling and simulation professionals and practitioners.

Michael Grieves · Edward Y. Hua
Editors

Digital Twins, Simulation, and the Metaverse

Driving Efficiency and Effectiveness in the Physical World through Simulation in the Virtual Worlds

Springer

Editors
Michael Grieves
Digital Twin Institute
Cocoa Beach, FL, USA

Edward Y. Hua
The MITRE Corporation
McLean, VA, USA

ISSN 2195-2817 ISSN 2195-2825 (electronic)
Simulation Foundations, Methods and Applications
ISBN 978-3-031-69106-5 ISBN 978-3-031-69107-2 (eBook)
https://doi.org/10.1007/978-3-031-69107-2

This Springer imprint is published by the registered company Springer Nature Switzerland AG
The registered company address is: Gewerbestrasse 11, 6330 Cham, Switzerland

Foreword

Through compelling real-world use cases and case studies, Dr. Michael Grieves, Executive Director of the Digital Twin Institute, an internationally recognized expert in the fields of Digital Twins and Product Lifecycle Management, first introduced the core concept of Digital Twins and further developed and evolved the concept and Dr. Edward Hua, Tech Lead for Digital Twins Simulation Engineering at The MITRE Corporation's Modeling and Analysis Innovation Center, has compiled a comprehensive history of Digital Twin foundational elements, concepts, methodologies, frameworks, and implementations in the chapters comprising *Digital Twins, Simulation, and the Metaverse: Driving Efficiency and Effectiveness in the Physical World through Simulation in the Virtual Worlds.*

Immediately insightful and impactful, this significant body of work, authored by experts in their fields, provides a cross-sectional view where Digital Twins deliver real value and transformative outcomes across diverse market sectors, segments, and industries.

With adoption spanning virtually every primary industry and new applications and use cases continually emerging, readers can understand Digital Twin's growth and adoption, including its near symbiotic relation to the evolving Metaverse landscape. The Metaverse is currently an evolving and not yet clearly defined concept. In the editors' introductory book chapter, the characteristics of Digital Twin Metaverses are outlined to provide a roadmap for the needed future development.

From conceptual methodologies, foundational elements, standardizations, and frameworks, including composability, construction, verification and validation, and other constructs spanning the different lifecycle phases, to exploring AI approaches—including prescriptive to autonomous, such as ML, as described through the application of Reinforcement Learning over the Digital Twin lifecycle—to Generative AI, utilizing co-pilots and multi-agents that deliver increasing value, traditional to intelligent Digital Twin use cases are revealed in highly informative detail.

These include an impressive array of examples that range from Nuclear facilities to Healthcare and Biomedicine, to Smart manufacturing—including the overall value chain along with advances in robotics and battery lifecycle production, to sustainable semiconductor fabrication and the Digital Twin role as “the photorealistic, physics-based, and real-time capable Digital Twin” where in turn simulation is the main ingredient of the Industrial Metaverse.

Examples of Digital Twin applications in Transportation management—Urban Mobility and Distributed AI Modeling and Simulation for Smart Airport Digital Twin with multi-agent transportation management systems, including Metaverse applications, are among several other use cases.

Learnings include the strategic integration of Digital Twins infused with AI and the significant role that reality capture plays in a pioneering journey of a NASA “factory Digital Twin,” where the Factory Twin’s value is realized and “positioned as a dynamic entity capable of substantial ROI.”

For those engaged in or interested in research, this book serves as a compass, helping to guide and provide an understanding of opportunities for both new and existing R&D pursuits. Each chapter includes valuable references for further investigation, pinpointing specific areas of interest.

Through evolving market and business landscape examples, this book further illustrates how industries are progressively innovating as new technologies—encompassing advances in extended reality (XR), AI, 5G, and Edge-Cloud Computing, among other enabling technologies—transform traditional business models and generate new opportunities.

Digital Twin characteristics, oriented to the Metaverse and viewed through a lens into the growth and evolution of this developing landscape, are presented. Historical and current market opportunities are detailed through specific areas of adoption across various APAC regions while also considering the developing future potential.

This compilation examines the development and progression of Digital Twins, including associated opportunities and challenges. The diverse collection of case studies and analyses provides insights into Digital Twin’s key role in digital transformation. Fueled by AI-accelerated growth and as exemplified by the use cases described, Digital Twin’s evolution and adoption show no signs of slowing, especially when coupled with the emerging Metaverse landscape.

San Francisco, USA
July 2024

Dan Isaacs

Contents

Defining, Exploring, and Simulating the Digital Twin Metaverses

Michael Grieves and Edward Y. Hua

Abstract This chapter presents a brief introduction and history of simulation, Digital Twins and their types and replica twins, and the origin of "metaverse". Underlying all these technologies is the premise that information generated by these technologies is a replacement for the wasted physical resources in human goal-oriented tasks. The chapter then provides the characteristics of a Digital Twin-oriented metaverse. It applies the characteristics to the different DT types. It concludes by discussing the evolution of Digital Twins in replication and prediction that will see Front Running Simulation as our crystal ball into the future. AI is predicted to play a major role in making this evolution possible as an assistance to humans but not a replacement.

Keywords Digital twin · Physical twin · Replica twin · Metaverse · Simulation · Front running simulation

1 Introduction

Digital Twins (DTs) are a twenty-first-century concept that has enjoyed an exponential growth of interest over the last decade. DTs originated as the underlying component of another twenty-first-century concept, Product Lifecyle Management (PLM). PLM represented a change from a functional-centric approach where each function, engineering, manufacturing, operations, and support had siloed its data and information to a product-centric approach where every function populated and consumed from a common source.

That common source needed to be DTs. DTs took advantage of the exponential increases in information technology to implement this lifecycle-based, product-centric representations of physical products and artifacts. This DT model was

M. Grieves
Digital Twin Institute, Cocoa Beach, FL, USA
e-mail: mgrieves@mwgvp.com

E. Y. Hua (✉)
The MITRE Corporation, McLean, VA, USA
e-mail: ehua@mitre.org

M. Grieves and E. Hua (eds.), *Digital Twins, Simulation, and the Metaverse*, Simulation Foundations, Methods and Applications, https://doi.org/10.1007/978-3-031-69107-2_1

originally proposed for automotive and aerospace. However, DT use has been proposed for almost any physical product or artifact that exists in the physical world, both tangible and intangible. The chapters in this book include DTs for industrial and manufacturing [1–4], nuclear reactors [5], health care [6], airports [7], semiconductors [8], power generation [9], and batteries [10].

Humans have always had physical representations of different scales and fidelity of products and artifacts in the form of Replica Twins as described later. DTs are a digital representation of counterparts that exist or are intended to exist in the physical world. Unlike atom-based objects where all or none of the objects exist, the bit-based data and information of DTs allow for granularity of representation. The fidelity of that granularity and the intervals needed to synchronize the DT and its physical counterpart will depend on the use cases that create value. In order to understand how value is created, it is important to understand what information does and the role information plays with the different types of DTs throughout the product lifecycle.

DTs have gotten a significant amount of attention from both academics and industry. However, equally important is a digital representation of the physical environment that the DTs are or will exist and operate in. While it is necessary and useful to have the data and information about the DT and its physical counterpart, it is equally important to understand the forces of the environment surrounding and affecting the DT and its physical counterpart. This means the creation of digital environments or digital spaces[1] that multiple DTs from different sources can interoperate in. These are what we are calling Digital Twin Metaverses that this chapter will describe. This represents the next wave of evolution for DTs.

While defining and exploring DTs and DT Metaverses are important, this evolution will feature the important capability of simulation. Simulation allows us to predict and anticipate the future, at least probabilistically. We have had simulations for as long as humans have been in existence and could think. What is novel is that we now have the technology to simulate outside of human minds with DTs. This chapter will set the stage for advancing this evolution.

2 Simulation

In the computer age, we technologists think that we have invented simulation. However, humans have been doing simulations since the beginning of their existence. Simulation is defined as one process that imitates another process [11]. It's important to note that processes are, by the very nature, time evolved. By that definition, simulation is a foundational aspect of human thinking.

[1] We will use virtual and digital as synonymous here. There actually is no true virtual space. The virtual representation is always instantiated in atom-based physical material. In humans, it's in the carbon-based matter of the brain. In digital computers, it's in the silicon-based matter of digital processor and memory components.

2.1 Simulation Through Human History

Since man began to think, he has performed simulations. Man has used simulations from the beginning of human existence for a wide variety of tasks. Simulation has been used for planning, assessments, training, scenario generation, risk assessment, experimentation, and even entertainment.

Take the example of prehistoric man hunting game. Prehistoric man ran through different scenarios in his mind of what he, his fellow hunters, and the animal would do. For example, the hunter mentally simulated what plan would predict running a mammoth off a cliff. He ran through various simulations of which hunters needed to be where, what actions they needed to take, and what reaction the animal would have. He then selected the simulation that he believed would have the highest probability of succeeding.

He shared that simulation with his fellow hunters by tracing his plan in the dirt with a stick. His fellow hunters watched this simulation unfold over time as the hunter traced the stick in the dirt, showing the movement of the hunters and their intended prey. It was crude. It was primitive. It often didn't predict the intended outcomes. However, it was simulation.

The history of the military is intertwined with simulations. Soldiers throughout history were trained in simulation exercises. Tzu [12] writes of convincing an emperor of his ability to train troops by doing a simulation using the emperor's harem. The D-Day invasion of Normandy Beach was planned via simulation in a Scottish harbor that had the characteristics of Normandy Beach [13].

Over history, humans developed more stylized simulations. Early Greek plays were simulations of what would happen over time when certain events took place. Later, in the Middle Ages, written stories were simulations [14]. In the 1900s, movies came about and provided much richer simulations that could be shared by many more people.

The arrival of computers in the last half of the twentieth century advanced the rigor and robustness of simulations. These simulations were mathematically oriented and could be quite complex in terms of calculations. However, these simulations with applications like GPSS were mathematically abstract, and visualization was limited to reams of numbers on paper output [15].

Fast forward to the twenty-first century. We can do very rich detailed simulations that provide photo realistic visualizations of the simulation of physical objects in their environments. These simulations reasonably mirror the changes of their physical counterparts when subject to the same forces.

2.2 Simulation Prediction—Causation and Correlation

As noted above, simulations are about predicting possible future outcomes. There are two mechanisms that simulation uses: causation and correlation. From a system's view of causation, we have inputs. We know those inputs cause specific things to happen in our system. We then get outputs. It is deterministic.

In the correlation model, we have inputs. We don't know deterministically what happens in the system, but we get outputs. Even though we don't know what happens within the system, we do know that there is a relationship between the inputs and the outputs. Varying those inputs will result in a varying of the outputs that maintain a correlating relationship. The correlations may be very strong, close to 100% or very weak, close to 0%. We can use strong correlations and ignore weak correlations.

We may have a correlation of 100% or close to that, but we may still not know why or how the inputs result in the outputs. These correlation models can be useful even if we have no idea why one input variable would correlate with an outcome variable [16]. Note that we are very uncomfortable and should be questioning correlations where we cannot theorize some relationship between correlated inputs and outputs.

Simulations can use both methods, causation and correlation. Simulation driven by causation will use formula or algorithms to take inputs and derive outputs. Simulation driven by correlation will take data that they have from previous input/output data and apply that to the input data that they are attempting to determine outputs for.

Causation will give deterministic outputs, while correlations will give probabilistic outcomes. However, it is important to note that for systems of high complexity, there may be other unknown causal variables that will affect the outputs. We may be unaware of these causal variables or that what we believe are causal variables are simply correlated with this unknown causal variable.

Many of the computer-based simulations in the past were driven by formulas or algorithms. The complexity of these simulations was such that this was sufficient for the outputs that were needed. The simplest version of this is $y = f(t)$. This could be an object moving in a straight line with a constant velocity. The variable "y" is the location at any time "t" produced by the function. While this is not usually thought of as a "simulation", it meets the requirements of the time-evolved definition. These functions or formulae can be very complicated but are causally deterministic.

However, as we get into more and more complex systems with numerous variables, some hidden, we will need to use correlations from big data that we are collecting from products that are in operation. As we collect more and more data from products in the field, Bayesian-based probability models assisted by Artificial Intelligence (AI) become more and more useful [17].

Using causation when we have it is highly preferred. However, it needs to be remembered that causal models are conditional and, for complex systems, may not reflect or predict accurately or capture all causal relationships [18]. Probabilistic correlation models can be highly effective in predicting overall successful outcomes. We can also use a hybrid approach which combines using both causal and big data correlations [19].

Going back to our prehistoric hunter, if he was successful 50% of the time in running a mammoth off a cliff but not knowing exactly why it worked, he and his tribe were well fed.

2.3 Front Running Simulation (FRS)

FRS is a specific form of simulation. FRS was introduced by Grieves [20] and is shown in Fig. 2. FRS is a simulation that predicts future states using assumptions based on physics and/or data. However, instead of the initial conditions of the simulation being arbitrarily set, the initial conditions are taken from the state of actual conditions in the physical environment. At every new time zero (t_0), FRS simulates future states and attaches probabilities to those future states. The future states that are the concern of FRS are states of adverse events. Adverse events are events that waste resources hindering or preventing us from completing our task goals.

There are two versions of FRS. The first is FRS using inputs from only the physical product itself to predict future states. The second is that FRS uses inputs from the physical product itself and the environment to predict future states. FRS acts as crystal ball into the future.

The specific conditions of FRS are:

- A simulation that contains behavioral assumptions of a corresponding physical product's future states based on physics causality and/or data probabilities, usually Bayesian based.
- The initial conditions of each simulation at t_0 are taken from the current state of an object in the physical world and, optionally, the environment that surrounds it.

2.4 Value of Simulation

Humans and non-human life, which for wont of a better term we will call "nature", have two different approaches to existence. Nature tries all possible combinations and lets the environment select the winners. Nature can do this because its only goal is survival of the fittest, and it has effectively an unlimited time horizon and resources. Nature also does not care about individual living organisms.

Humans, on the other hand, do care about individual living organisms, especially their own. Humans do not have unlimited time horizons and resources. Humans also have other goals besides survival. The human approach is to be task goal-oriented and to accomplish that task using the minimum of physical resources, time, energy, and materials.

Given that Is the case, the human approach means that for a goal-oriented task, humans employ sophisticated thinking capabilities utilizing data, information, knowledge, and wisdom (DIKW) [21]. This relies on the fact that the expended physical resources used to perform the goal-oriented task can be divided up into two categories. These two categories are shown in the left bar in Fig. 1 [22].[2] The lower part of the bar is the minimum amount of resources that is ideally required to

[2] The figure in the book had a third category, Execution Inefficiencies, where we know what we need to do to eliminate the waste but don't have the technical capabilities yet to do so. That category was dropped in later versions in the interest of simplification.

complete the task. Everything above that is in the second category of wasted physical resources. We can apply a cost function to this in order to value the time, energy, material of the physical resources needed to accomplish the task (Fig. 2).

The right-handed bar shows the role of information in task accomplishment. The amount of physical resources necessary to accomplish the task in the most optimal fashion stays the same. Information cannot replace the minimum amount of physical resources necessary to complete the task. However, information can replace the information inefficiencies or wasted resources ($C_w(x)$) over and above that. For purposes of illustration, this figure shows information as replacing all the wasted resources, but for human endeavors, this will usually not be possible.

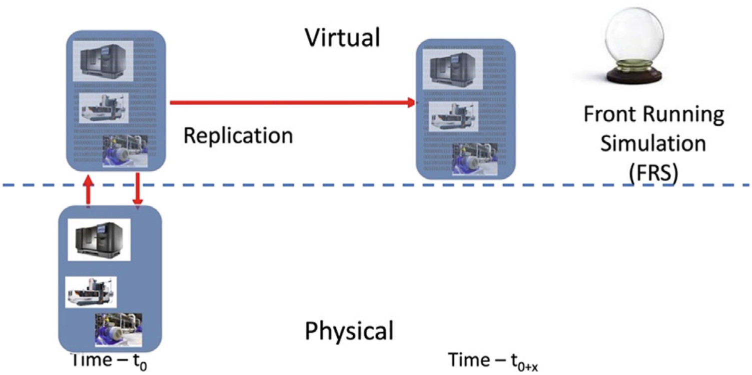

Fig. 1 Front Running Simulation (FRS)

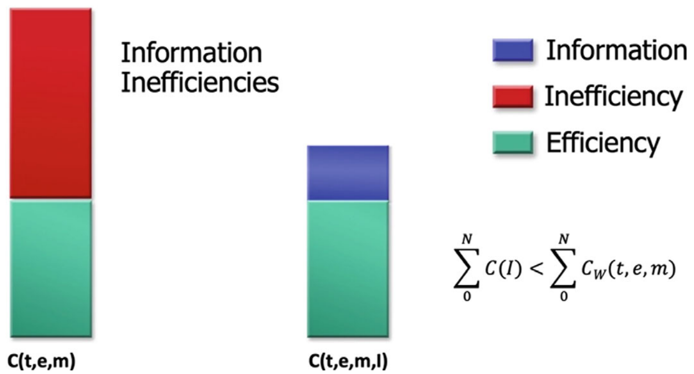

Fig. 2 Information as time, energy, material trade-off

The issue with this costing function is that the cost of generating information from data[3] does not come in a unit of measure, like physical resources. We can use time and physical resources needed to develop this information as a proxy for a unit of measure. In the past, that proxy has always been human resources and physical materials. Today, the proxy commonly consists of computer hardware, software, and energy in addition to human resources. As represented in the formula, the assumption under which this model holds true is that the cost of developing this information is less than the cost of wasting resources over all the times the task is performed.

Simulation is a method of developing information. Humans have no interest, let alone the resources, in trying all possible combinations and letting the environment dictate which one is successful. Humans want to simulate the possible ways of obtaining their task-oriented goals and then perform the task using the method that minimizes their scarce physical resources of time, energy, and material.

Throughout all of human existence, until very recently, those simulations involved only the computational capabilities of human minds. The development and rapid advancement of digital computing bring a quantum leap in simulation value for human goal-oriented tasks. The more accurately predictive and cheaper that their simulations are, the greater value humans will obtain in completing their goal-oriented tasks while minimizing the use of physical resources.

3 Digital Twins

The concept of twins is ontological. We constantly categorize and compare things to see if they are similar, so we can make decisions about how we should interact with them. We expect to find similarities and regularities in our world. If we could not, the world would be a very lethal place [23]. "Twin" is the regularity that something is identical or nearly identical to something else, so that we can apply how one of the twins looks and/or behaves to the other twin.

The only requirements for a "twin" are that it has two key attributes: duality and strong similarity. That is there needs to be two of them, and they need to share significant attributes. There is no ontological or metaphorical requirement for timeline simultaneity, as in human twins, scale similarity, or for the precedence of one type of twin before another type of twin, e.g., a Physical Twin before a Digital Twin.

[3] There is much confusion about what is data and information. We have a functional perspective. Data is a fact or facts about reality and the input to create information: We collect data and process it to create information. Information is a replacement or substitute of wasted physical resources: We use information.

3.1 Replica Twins

There are physical objects that are "twins" in the sense that they are simply independent duplicates. What we are interested in is 3D physical objects that are intended to represent a specific physical object.[4] Since the term "Physical Twin" (PT) refers to the physical object in the dyad of Physical Twin–Digital Twin, we will call these 3D physical objects Replica Twins (RTs). We will use Replica Twins (RTs) in the sense that there is a unique physical object and a replica physical object that can be at different scales and fidelities.

RTs, even if primitive, rudimentary, and abstractly shaped, have been used in human endeavors for all of human existence. RTs have been used at all scales, from small models to full-size replicas and all fidelities, from exact replicas to simple representations. While barely three-dimensional, prehistoric man sketched in the dirt with a stick a representation of a mammoth, the cliff that the mammoth needed to be driven over, and the positions of his fellow hunters. While military sand tables date from the 1800s, equivalents date back to ancient Greece military use and most likely before.

Architecture has used RTs from earliest times all over the world. RT artifacts have been discovered dating from at least 6000 BC. RT model making was prevalent in ancient Greece. The making of RT models to represent actual physical buildings existed throughout the world in all cultures [24].

The RTs were even dynamic and not simply static. Watch any movie about World War II. It will generally feature a table with a geographical map that people will move around representations of military and naval forces. As dispatches come in, people move these representations into different geographical positions so that commanders can assess and plan their next strategic and tactical moves.

But it wasn't simply scale models that were replica Physical Twins. Full-scale RT mockups have been created and used. Full-scale RTs have been used in military preparation as long as military engagements have existed. As noted above, the D-Day preparation included exercises on Scotland beaches that were the replica physical "twin" of Normandy Beach.

As discussed in the simulation section above, we could argue that since very early times plays, and then later, in the twentieth century, movies have used full-scale RTs in a form of simulation. Plays and movies have created exact replicas of existing physical environments and then "simulate" activity within those environments. For example, an exact replica of the US White House Oval Office appears in an innumerable number of movies and television shows.

For equipment and vehicles, RTs were used primarily in development. However, RTs were also used to resolve issues with operational equipment and vehicles. Airplane manufacturers used replica twins to recreate and troubleshoot reported

[4] Obviously, there have always been 2D representations of physical objects, such as sketches, drawings, blueprints. However, we wouldn't call them "replicas", as humans must do much mental work to visualize them even poorly as three dimensional. They are more accurately described as abstractions.

problems with their airplanes in the 1930s. When problems were reported with automobiles, it was standard operating procedure for the engineer working on the problem to find an identically configured automobile to try and recreate the problem.

As we developed electronics, we could make these RTs dynamic on their own. The company one of the authors worked for in the 1970s, Lear Siegler Corporation, had an F-16 flight simulator in its Grand Rapids Instrument Division. It was physical, not digital. However, dynamic flight simulators date back to the 1930s with the Link simulator [25]. There have been dynamic replica Physical Twins of nuclear reactor control rooms for training and emergency exercises for over 50 years [26].

The Apollo program is often cited as the first use of Digital Twins. That myth is still being perpetuated today.[5] The common reference is to the Apollo 13 mission, where the myth is that its "digital twin" was used to bring the crew safely back home after an almost catastrophic malfunction.[6]

The reality is that the digital capabilities of the most powerful computer mainframes of the Apollo days were extremely limited compared to today. Main memory of the most powerful mainframes of the era was in the 16 MB range. The Command and Lunar Landing Modules had a miserly 2K of main memory. The extensive troubleshooting on earth was done with a series of RT capsules that had no "digital" aspects.

Replica twins have been in existence throughout humanity's history and are still in use today. Replica twins have been abstracted in such representations as dirt sketches and sand tables. Replica twins have been realistic scale models such as buildings and even cities. Full-scale replica twins have been used to prepare for and track military engagements. Replica twins have existed dynamically as in the Link, F-16, nuclear reactor control rooms, and the Apollo space capsule simulators. The advent and rapid development of digital computers enabled the logical next step of moving "twins" from physical replicas to digital ones.

3.2 *The Rise of Digital Twins*

Digital Twins are a twenty-first-century concept. While considered a possibility since the early days of digital computers [27], it isn't until the 2000s that a cohesive model and concept were proposed.

There were two major capabilities that DTs were intended to have: replication and prediction. Replication is the characteristic that the DT would possess all the data of

[5] This can be independently verified by doing a search of academic papers using the keywords "digital twin" and "Apollo".

[6] Apollo 13 might be the most amazing malfunction recovery story ever. One of the authors had the privilege of meeting the Apollo 13 Commander, James Lovell, and hearing first-hand the amazing story of two astronauts sitting on what was basically a couch in Apollo 13, lining up the earth's meridian vertically and horizontally perfectly on a reticule etched on Apollo 13's window so that they didn't burn up or bounce off into space at re-entry. However, the "twin" involved in working the problem on earth was a replica twin capsule simulator, not a digital twin.

its physical counterpart needed for use cases. At its ideal, any data that could be had while in physical proximity of the physical counterpart could be obtained from its DT. The characteristic of prediction is that the DTs would causally or probabilistically predict the future states of their physical counterparts.

The origin of the Digital Twin model is well documented in a multitude of academic papers and industry articles [28]. Figure 3 is the first version of the Digital Twin model that was presented at a Society of Manufacturing Engineering (SME) conference in Troy, Michigan in October 2002. The presentation was entitled Completing the Cycle: Using PLM Information in the Sales and Service Functions [29]. It was about using Digital Twins in the operational and support phase of the product lifecycle when there was both the physical product and its Digital Twin.

The model in Fig. 4 was refined a little later that year to emphasize that products existed in real and virtual spaces. This version was for a meeting of industry executives, automotive software providers, and academics from the University of Michigan. The meeting was to explore setting up the Product Lifecycle Management Development Consortium (PLM DC) at the University of Michigan. Because of the automotive industry attendees, the focus was on different product lifecycle phases than the SME conference, namely engineering and manufacturing.

Both presentations were about the new discipline that was being defined, Product Lifecycle Management (PLM). As a result, the model did not even have a name, as it was simply entitled "Underlying Premise of PLM". It did describe that the model's

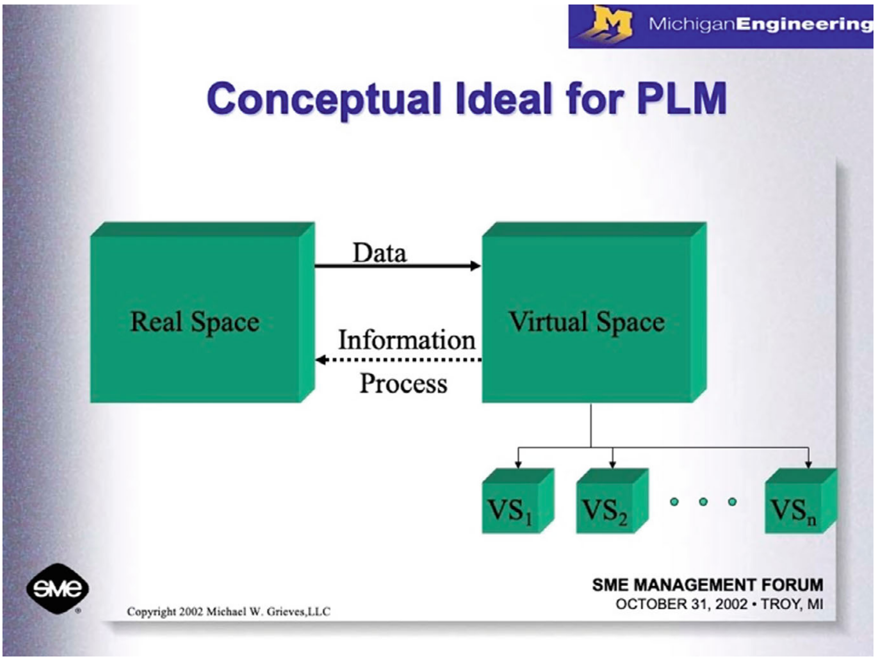

Fig. 3 Original Digital Twin model

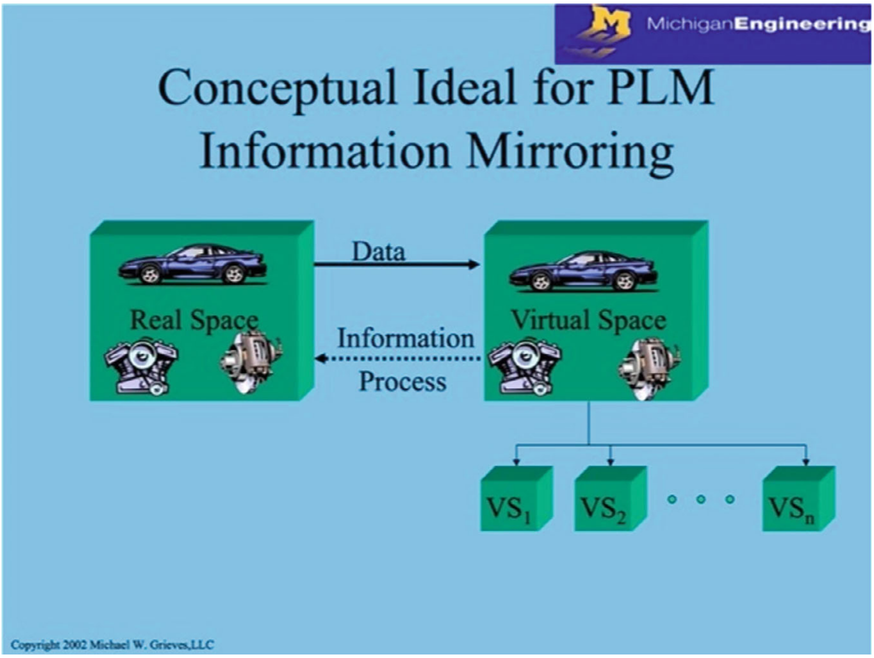

Fig. 4 Original Digital Twin model version 2

purpose was "Information Mirroring". Even though it was rudimentary, the model contained the major elements of the Digital Twin that exist today.

On the left side were physical products in physical space. These are the Physical Twins (PTs). On the right side were virtual products, which we now refer to as Digital Twins, in virtual space that corresponded to the physical products. The third element is that there were communications between the two spaces and products, with data from physical space and products obtained from sensing and IoT devices populating the virtual space and products, and data and information coming back from virtual space and products to be used in the physical space.

These models also contained the sub-spaces as part of the virtual space, VS_1, VS_2, VS_3… VSn. The idea of virtual spaces was fairly new at the time, so this was to emphasize the fact that while there was only one physical space, there could be an unlimited number of virtual spaces.

This model highlighted that there were two main functions that it implemented: replication and prediction. Replication is the characteristic that the DT would possess all the data of its physical counterpart. The products in physical space were replicated by the products in virtual space. At its ideal, any data that existed in the physical product was replicated in its Digital Twin.

The characteristic of prediction is that the DT would causally or probabilistically predict the future states of the physical counterparts. The subspaces were virtual

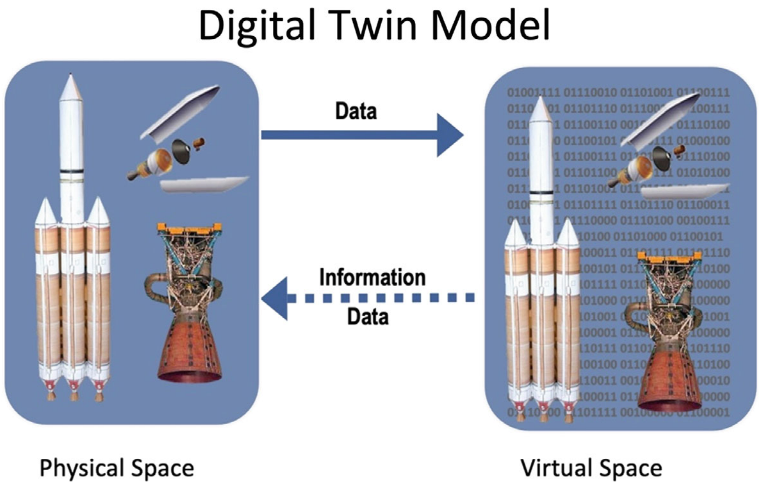

Fig. 5 Current Digital Twin model

areas where predictive simulations could be performed. The multiple subspaces were indications that there was no limit as to the number of simulations that could be done.

The model was changed during work at NASA. The graphics are better, courtesy of NASA, when the model was used for a Department of Defense (DoD) conference [30]. In addition, the model was also simplified, as shown in Fig. 5. It was felt that sub-virtual spaces unnecessarily complicated the model. However, as we will explain later, the original model better represents a metaverse model.

While the model did not have a name originally, it did acquire some names shortly thereafter. It was called the Mirrored Space Model first, and then shortly thereafter that was changed to Information Mirroring Model. The Information Mirroring Model name remained albeit somewhat obscurely until around the 2010 timeframe. At that time John Vickers of NASA who was working with Grieves suggested the name Digital Twin. The Digital Twin name was a replacement for the relatively strange name that NASA was using, Virtual Digital Fleet Leader.

The Digital Twin name was mentioned in a footnote in Grieves' book on PLM [31], attributing the name to John Vickers. Grieves used the Digital Twin name in one of the seminal and highly cited Digital Twin papers [32], which noted that the Digital Twin name was going to be used for the model from then on. Later, in a short but highly influential piece, Grieves wrote an article for the Economist Magazine in the GE Lookahead section that was subsequently picked up by the World Economic Forum [33]. The Digital Twin was explained to the general audience in that short article.

2015 marks the beginning of an exponential growth in reference to Digital Twins in academic papers, industry white papers, and websites. The uses of DTs were initially proposed for aerospace and automotive. That has exploded to encompass a huge swath of industries and disciplines: power generation, heavy machinery, smart building/cities, oil and gas, ports and airports, archeology, and healthcare, just to name a few. Doing an internet search of “Digital Twins” in 2018 resulted in only one million hits [34]. A search of 2022 results in over 17 million hits. The number of academic papers on Digital Twins shows a similar exponential growth (2015—295 results, 2022—17,100 results).

As of today, the model in Fig. 5 is the accepted model of the Digital Twin. While definition may vary and vary widely, images usually show Digital Twin representations that are fairly consistent in the representation of physical space and products, digital space and products, and a two-way connection between them.

The commonly accepted Digital Twin Model that was introduced in 2002 and simplified to the one as shown in Fig. 5 consists of three main components:

- The physical products (PT) in the real-world environment.
- The Digital Twins (DTs) in a digital environment.
- The two-way connection between the physical and virtual for data and information.

The third component, the connection between the physical and digital has often been referred to as the “digital thread”. The connection is a two-way communication connection. Data from physical products and their environment is communicated to the digital environment and populate their DT counterparts for collection, assessment, and response (CAR) [20]. Data and/or information (if action to replace physical resources is proposed) is now available to the physical environment.

The digital environment of the Digital Twin, referred to as the Digital Twin Environment (DTE), requires that it has rules that are identical as possible to our physical environment. We need to be assured that the behavior of the Digital Twin in the DTE mirrors the behavior of its physical counterpart for the use cases we require.

Finally, it is important to remember that when we refer to Digital Twins in a general way, we are implicitly including all three elements of the Digital Twin Model. We are not simply referring to the digital object that represents a specific physical object. While it would be more accurate to use the term, Digital Twin Model, we simply us Digital Twin.

3.3 Types of Digital Twins

There are three types of Digital Twins: the Digital Twin Prototype (DTP), the Digital Twin Instance (DTI), and the Digital Twin Aggregate (DTA).

The DTP originates at the creation phase of the product lifecycle. The DTP of a product begins when the decision is made to develop a new product, and work begins doing just that. The DTP consists of the data and information of the product’s physical characteristic, proposed performance behaviors, and the manufacturing processes to build it. The DTP should also include the necessary processes and practices to ensure the product is fully supportable and maintainable in the field and to troubleshoot and repair the product effectively and efficiently to keep it operational. As much of this work as possible should take place virtually.

The DTI originates when individual physical products are manufactured. DTIs are the as-builts of the individual products and are connected to their corresponding physical product for the remainder of the physical product's life and even exist beyond that. The DTI implements replication. Much of the DTI can simply be linked to the DTP. For example, the DTI can link back to DTP 3D model and only needs to contain the offset of exact measurements to the designed geometrical dimensioning and tolerance (GD&T).

Pre-production physical product versions that are called physical prototypes will have a DTI since these are actual instantiations of the developmental period. These DTIs should be put to the equivalent digital tests and evaluations as the physical prototype itself. Comparing the digital results to the physical results will increase the confidence on relying on digital testing when the product is moved to full rate production. Where there are significant deviations, digital testing can be improved to converge on producing equivalent results to physical testing, with the goal of dramatically reducing and even eliminating physical tests, except for a final physical validation.

The DTP will contain the manufacturing process, Bill of Process (BoP), and the parameters associated with the BoP. The DTI will contain any variations that occurred in actual production. For example, the DTP process may require heat treating within a temperature range. The DTI will capture the temperature that actually occurred. The data and information that is needed for the DTI will be driven by the use cases of the organization. The digital testing described above will make it possible to test digitally each DTI of its physical counterpart to enable a high level of confidence in the future performance of each individual product [35].

Because the DTI remains connected to its physical counterpart for the rest of that physical product's life, it will also contain the data from its operation. The DTI will contain sensor readings and fault indicators. Based on use cases, the DTI will contain a history of performance of state changes and resulting outcomes.

The DTA is the aggregate of all DTIs. The DTA contains all the data and information about all the products that have been produced. The DTA may or may not be a separate information structure. Some of the DTA data may be processed and stored separately for analysis and prediction purposes. Other DTA data may simply be mined on an ad hoc basis.

The bigger the population of DTIs, the more data that will be available to improve Bayesian-based predictions. The DTA, which consists of the DTIs of physical systems, is subject to model bias for its predictions. However, there are mathematical techniques available for bias identification in DTs [36]. The DTA will also be the source for Artificial Intelligence and Machine Learning (AI/ML) to predict expected performance.

In 2019, Grieves introduced the Intelligent Digital Twin (IDT) to explain the role that AI would have in both assisting Digital Twins in their performance and in dealing with the increasing system complexity and emergent behavior of products themselves [37]. The view here was that AI was not a replacement for humans but an augmentation for humans. IDT specifies four attributes for Intelligent Digital Twins as active, online, goal-seeking, and anticipatory.

The characteristic of anticipatory requires that the Intelligent Digital Twin can be constantly running simulations to look ahead into the future for its PT. That obviously means that FRS is a critical component of Intelligent Digital Twins.

3.4 Digital Twins and Simulations

As defined above, simulations are one process that imitates another process. In the case of Digital Twins, we require that the "process" we imitate is our physical universe. Our DT simulations need to have as perfect fidelity to the laws of our universe as we need for our use cases. The characteristics of materials and forces of our physical universe need to be imitated as closely as possible. Simulation is what is needed to implement DT prediction.

The one exception to adherence to the laws of our universe is the cadence of time. We are unconstrained by time [37]. In our physical universe, time is completely out of our control. We cannot go back in time. The only way to go forward in time is to wait for the next tick of the clock. Even then, we go forward only according to the set time. We cannot slow time down nor speed it up.

In digital spaces, we are time unconstrained and can completely control time.[7] We can run our simulations at any clock speed. We can computationally go years and decades into the future. We can also slow down time. We can break down actions that happen in split seconds in our physical universe into microseconds.

In digital space, we can even go back in time which we cannot do in physical space. In the physical world, we employ forensic methods to attempt to determine what happened in the past that resulted in the current present. In simulations with deterministic rules, we can usually reverse the arrow of time in the digital world. If we have been using traceability to capture state changes, we can simply step back through the time frames.

However, another fundamental advantage is prediction, being able to advance the clock to see what's going to happen in the future. This is a crystal ball that sees into the future. With Front Running Simulation (FRS) described previously, we have the ability to do just that.

The assumption is that "simulation time and wall clock time can be kept in sync using conservative and optimistic synchronization protocols" [38]. At every new time t_0, we will be able to take the data from the physical world, i.e., replication, and predict at least probabilistically what will happen in the digital world. This is a tremendous opportunity to prevent the waste of physical resources by anticipating

[7] I discovered this firsthand in the early 1970s. Even though I was only a sophomore in college, I was a systems' programmer for a computer timesharing company. We charged by the CPU second. There was a meeting to discuss how to increase revenue. After listening to the staff provide ideas, I simply said, "I can increase what a CPU second is". That worked in increasing revenue until some customers started running benchmarks and complained that their programs were taking more elapsed CPU seconds and therefore were more expensive to run!

and correcting adverse events, especially ones involving the safety of individuals, before adverse events can occur.

3.5 Digital Twins, Simulation, and Information

The purpose and value of DTs are that they provide information that can replace wasted physical resources. One of the three elements of the Digital Twin Model in Fig. 5 is the connection between Physical Space and its Physical Twins and Virtual Space and its Digital Twins. Data is sent from the physical products and optionally the physical environment to the digital DTIs. The information that is created and housed in digital space is used in our physical space. This information is created by processing the data coming from the physical space and, as noted above, by performing simulations.

This information can take a couple of forms. It can be the result of humans doing queries of DTs and creating information by using the result of the queries to take action that will replace wasted resources.

For example, a certain model fuel pump of a helicopter is being recalled and replaced. The traditional method would be to identify the location of every helicopter, send a mechanic to inspect each one, and replace the fuel pumps in the helicopters with the defective ones. With DTs, a query would be run on all the DTIs. Mechanics would only be sent out to only those helicopters with defective fuel pumps. That results in information replacing the wasted physical resources of mechanics' time and expenses for the helicopters with fuel pumps that need no replacing.

Information can also be created by routines that run on a constant basis in digital space looking for specific sensor data patterns that, using physics and DTA data, simulates and predicts adverse events and alerts humans to them. Humans have the responsibility of deciding the actions to take to avoid wasted physical resources by having an adverse event occur. This is a human-in-the-loop version.

The information can also be routines that run in digital space that specify actions to take when they find certain conditions. These actions are coded as commands and sent to the PTs directly, without human intervention. FRS is applicable in both simulation-based situations. All are the result of data coming from the physical world to digital world and data and information returning from digital world to the physical world to replace wasted physical resources.

4 Metaverse

"Metaverse" is a portmanteau of "universe" and "meta". "Universe" would commonly be thought of as our one and only ("uni") physical universe. "Meta" is having aspects or capabilities that transcend or are beyond the ones our universe possesses.

Like Digital Twin, "Metaverse" is a twenty-first-century term. Although "metaverse" has its origin in the last decade of the twentieth century as described below, "metaverse" only starts to be prominent in the last few years. The metaverse, virtual spaces, virtual worlds, digital spaces, and digital worlds have been used fairly synonymously. All these terms refer to virtual representations of the physical world. As explained in Product Lifecycle Management: Driving the Next Generation of Lean Thinking [39], humans have had virtual spaces since the beginning of their existence.

Humans have always had the ability to virtually represent the physical world in their own minds. However, those representations suffer from vagueness, impermanence, and an inability to share with other humans. The result was that whenever we developed a mental model or a new idea, it had to take immediate physical form in some fashion: a sketch, a drawing, a blueprint, or a physical model.

4.1 Origins of Metaverse

The term, "metaverse" is almost universally attributed to originating in Neil Stephenson's book, Snow Crash [40]. Stephenson's metaverse is a singular space where an individual as an avatar interacts with other avatars in an immersive environment. The immersive environment was implemented by a Virtual Reality (VR) headset that the user wore.

This type of metaverse was almost exclusively about social interaction. This was described in a contemporaneous definition of "virtual worlds", which defined them as, "A synchronous, persistent network of people, represented as avatars, facilitated by networked computers" [41]. The virtual worlds and Stephenson's metaverse were synchronized with our physical world, could not be paused, and existed for the interactions of people as avatars.

There was some correspondence with our physical world in that it had three dimensions, and inanimate objects had persistence and impermeability. Avatars could move about in this three-dimensional space. There was a monorail that traveled the entire metaverse space and other vehicles were available, although how avatar locomotion itself was accomplished was never really explained [42]. Like Linden's Second Life, users could acquire virtual real estate where they could construct virtual buildings and other virtual artifacts [43].

Stephenson's metaverse had its own laws that loosely, if at all, followed the laws of our physical universe. For example, one can be driving a motorcycle at Mach 1 speed, run into a metaverse building, and the motorcycle and rider simply come to a stop with no damage to anything.

In the years after Stephenson's book and specifically within the last few years, metaverse has become synonymous with almost any and all digital spaces. This has led to the term "metaverse" applying to all digital spaces even if they are in contradiction to each other.

There has been discussion of an "Industrial Metaverse" that is vaguely defined as "the set of metaverse applications designed for industrial users" [44] [45]. The descriptions on an Industrial Metaverse almost always focus on technologies that users can exploit such as Augmented Reality and Virtual Reality. But there is a lack of defining what is required for such a metaverse. This needs to be much more concrete as we will discuss below.

4.2 Metaverse and Digital Twins

The original view of the metaverse is substantially different from what is required for the purposes of Digital Twins. There is no reason that there cannot be all types of metaverses with different rules governing them. The rules can be completely arbitrary and have only a tenuous connection with our physical universe, as was the case for the Stephenson metaverse.

However, we would contend that we can legitimately co-opt the term because our metaverse required for DTs has more fidelity to the meaning of the words, "meta" and "universe". What we require is a digital fidelity to our physical universe with meta capabilities. The metaverse that we require needs to have complete conformance to the selected rules of our unitary, physical universe, although it can have meta capabilities as described below.

In order to move work from the physical world into the digital world successfully, the metaverse of Digital Twins needs to enforce all the laws of our physical universe required by the supported use cases. However, we need a metaverse that is specifically tailored to Digital Twins. From now on, we will refer to this type of metaverse as a "DT Metaverse" (DTM).

As humans perceive it, our universe is a three-dimensional space populated by objects. The DTM will have that same characteristic, a three-dimensional space populated by DTs. This will allow humans to use their ontological understanding of physical space to understand and operate seamlessly in the DTM.

Figure 6 is an evolutionary model of the DT that has been proposed previously by Grieves [27]. The claim is that we are currently in Phase 2, the Conceptual Ad Hoc phase. This is the current state of DT evolution.

In this phase, "the Digital Twin is an entity that we conceptually create from disparate and even fragmented data sources. We use different existing sources to pull data from. We start building correlations and even causations of data source inputs to results. We build different simulation views and determine how well they map to reality. We start to put manual processes in place to pull the data from different sources, even if on an ad hoc basis, to create a Digital Twin view [27].

The next phase in the evolution of DTs is the creation of DT platforms. These platforms are envisioned to support multi-users and multiple DTs. DT systems are possible in Phase 2. However flexible Systems of Systems (SoS) where multiple DTs of completely different functions enter and exit will require platforms that support interoperability.

First will come platforms that support replication, Phase 3. Those platforms will be followed by platforms for prediction, Phase 4. While not referred to as "DT

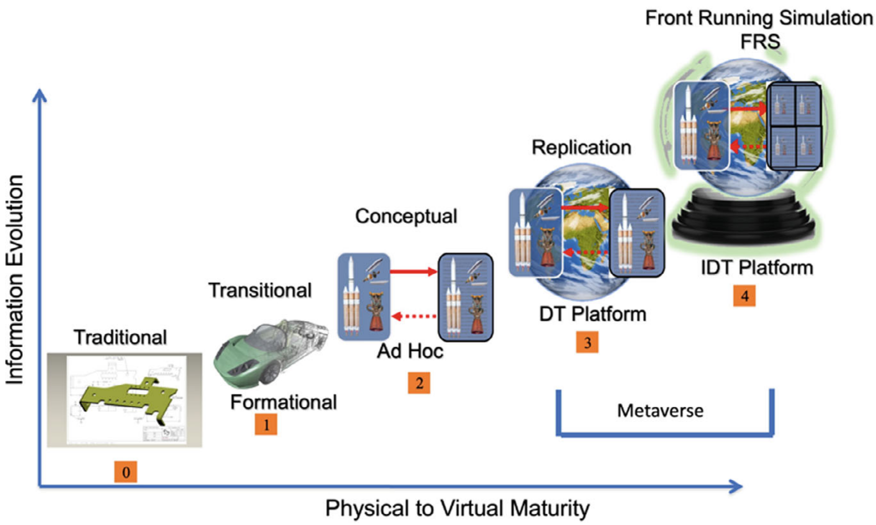

Fig. 6 Digital twin evolution

Metaverses", that is in essence what these platforms are by our definitions here. These platforms now have a name, DT Metaverse. They are consistent with the long-term vision of DTs.

The DT Metaverse has these key characteristics:

- There are multiple DT Metaverses.
- DT interoperability is a core requirement.
- All laws of the physical universe are implemented and enforced in simulations for all inanimate objects.
- The DT Metaverse supports both replication and prediction.
- Multiple immersive participants as avatars is supported.
- Meta capabilities are allowed for human participants as avatars.
- Time can be synchronous or asynchronous with physical time depending on use case and DT type.
- Cybersecurity is embedded in all aspects of the DT Metaverses.

4.2.1 There Are Multiple DT Metaverses

The limitation of our physical universe is that there is only one. If the Many Worlds theory is correct and multiple physical universes exist [46], we will only ever have access to the single physical universe this version of us inhabits. In the digital universes, we can recreate our physical universe at some level. Since we have no physical restrictions on the number of computer-based spaces, we have no restriction or limitation of the number of digital metaverses that will be available to us.

As the original DT model proposed, we have effectively an unlimited N number of sub-virtual spaces. Ironically, the original Digital Twin model in Figs. 3 and 4 is a much more accurate model of the DT Metaverse than the simpler model in Fig. 5 that is evolved from it.

We expect that there will be many different metaverse platforms in the near future. They will be differentiated by different use cases, different DT types, and different phases of the product lifecycle. DT Metaverses can be on a spectrum of completely private to completely public. While we are restricting our discussion to DTs of tangible products, there is no reason that metaverses for intangible or process DTs such as supply nets, manufacturing processes, or financial systems cannot be developed. If we can visualize the data and information in some symbolic fashion, we can have a DT Metaverse for it.

4.2.2 DT Interoperability Is a Core Requirement

The concept of a DT Metaverse implies that there will be multiple DTs in it. Otherwise, the DTM would be no different than what we have today, which is a Phase 2 Conceptual Ad Hoc programming space. The ability to easily insert a DT into a digital environment to monitor its interaction and behavior with other DTs will greatly enhance their value and usefulness. Interoperability also implies intra-operability as this will also foster component modularity within DTs.

This means that the DT Metaverses are platforms. Platforms are hardware and software infrastructure that provides underlying tools, services, and governance to accomplish participative specific tasks and interactions [47]. Participative implies that there is intended to be multiple users and multiple DTs. So, this means that the platforms need to enable the interoperability of DTs.

There are numerous organizations working on mechanisms for interoperability. A common perspective for interoperability is to produce standards and ontologies. While this works in the physical world, it is much more difficult in the digital world because of the much finer granularity of data and information. As a result, to address this, we have a multitude of standards, which means that we really don't have "a" standard.

These other mechanisms that platform may employ include defining ad hoc programming conventions, harmonization of programming conventions among software providers, and a platform's own middleware. A promising solution may be to deploy AI. AIs may be able to explore the solution spaces between different DTs and provide mapping and translations. As Fig. 7 illustrates, AI may provide both intra-operability for components of a Digital Twin and interoperability for different DTs in DTMs.

Depending on the DT type and use case, the DT Metaverse will be useful for its ability to support immersion for multiple people assessing the serviceability of a new product. It may also be useful for staging and operating multiple products in simulation from different vendors in virtually commissioning a production line.

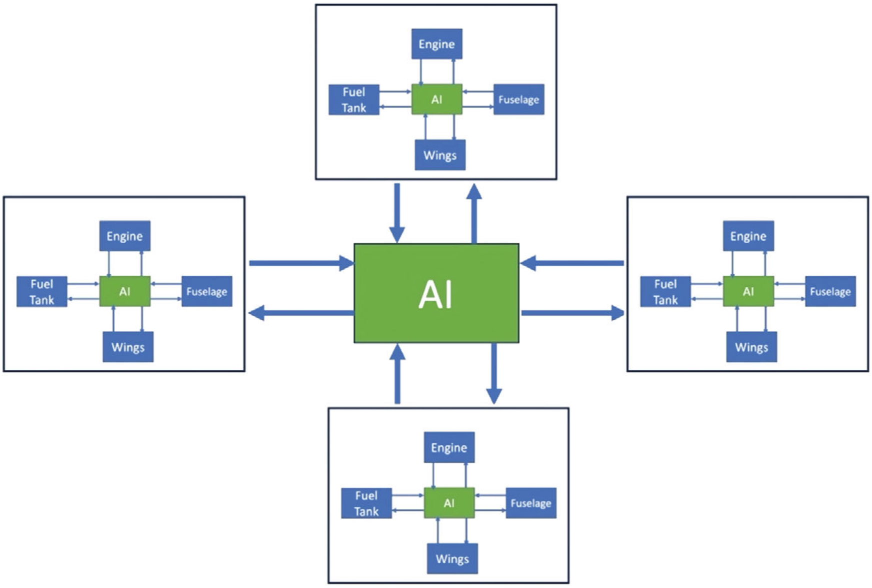

Fig. 7 AI DTM interoperability at the system of systems level

4.2.3 The DT Metaverse Supports Both Replication and Prediction

There are two main characteristics that DTs need. Those characteristics are replication and prediction. Even if a product is being developed in digital space and has not yet taken physical form, the environment that the new product is going to exist in needs to replicate our physical universe for the use cases needed.

When we have DTIs of existing physical products, we need to replicate the data from those PTs that we require for our use cases. The DT Metaverses supporting this will be on a spectrum. On one end, there is simply the DTI in empty space that can be simultaneously and instantaneously interrogated no matter where its PT is in the physical world. On the other end of the spectrum, we can have DTIs and the surrounding environment it currently resides in that an immersive avatar can experience.

We need prediction both when we are developing the product and then when we have a product that is in operation. We need to predict what forces that the product produces will have on its own structure, its operation, and its surrounding environment. We also need to predict the impact that outside forces we'll have on our product. Prediction is done via time-evolved simulations and can be done based on hybrid physics/data probabilities techniques. Again, the DTM will be on a spectrum from simply having the DTI representation of PT itself to having the DTI representation of PT and its current surrounding environment. This gives us the ability to be time and space unconstrained with a probabilistic window into the future.