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SIMULATION-DRIVEN DIGITAL TWINS: THE DNA OF RESILIENT SUPPLY CHAINS

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ABSTRACT

This tutorial defines what a digital twin is and outlines its four required characteristics. Digital twins are developed to derive insights to control entities and processes in the digital world with simulation as one of the key technologies lying at the heart of this development. The resulting insights are used to prescribe actions in the physical world to fix future problems before they happen. This tutorial describes the key digital twin development functions together with the digital twin enabling technologies with focus on the use of simulation for process twin development. The corresponding functions and technologies are displayed on several different digital twin development frameworks with the potential to serve as guides for practitioners interested in developing digital twin solutions. We conclude with an example of a supply chain digital twin use case and the role of simulation and AI in the twin development.

1 INTRODUCTION

Global Market Insights (2020) reports that the digital twin market size exceeded $5 billion in 2020 and is expected to grow at over 35% compound annual growth rate between 2021 and 2027. McKinsey (2021) expects digital twin adoption to unlock $5.5 trillion – $12.6 trillion globally by 2030. These estimates are vastly different from each other; however, it is apparent that digital twin will play a paramount role in companies' digital transformation efforts in the years to come. According to Gartner Prediction, 25% of healthcare delivery organizations will include formalized digital twin initiatives within their transformation strategy (Lazer 2023). Digital twins are further expected to be the building blocks of the industrial metaverse (Fast Company 2023). Thus, it is more critical than ever to understand what a digital twin is.

The Digital Twin Consortium defines digital twins as virtual representations of real-world entities and processes synchronized at a specified frequency and fidelity (Digital Twin Consortium 2020). An example of a real-world entity may be an individual asset such as an industrial machine. Its virtual representation would be called "asset twin" as it approximates the behavior of a physical asset. Digital twins can also represent systems of physical assets such as a factory or a supply chain network of suppliers, factories, warehouses, and customers. Because these types of digital twins are built to represent business process flows and capture the interactions of physical assets in the corresponding systems, each of them is called "process twin." Furthermore, a process twin representing a manufacturing process flow in a factory is often called "factory twin" while a process twin capturing a supply chain flow is called "supply chain twin."

A natural question to ask is " what are the major benefits of the digital twin technology?" Very briefly, digital twins aid in deriving insights to control entities and processes in the digital world and use those insights to drive actions in the physical world. Digital twins are used to understand what did happen, predict what may happen, and determine solutions to fix future problems before they happen. More specifically, asset and process twins can be used (i) to predict key performance indicators (KPIs) and gain visibility into the future health of assets and processes, (ii) to assess the impact of operational policy, design, and investment decisions in a virtual environment, and (iii) to stress test assets and processes under consideration and identify best courses of action to take when faced with disruptions. The ability to provide real-world feedback to digital twin models of assets and processes about the effects of their solutions implemented in the physical world is key to achieving these objectives. The adoption of emerging technologies such as Internet of Things (IoT), edge, and cloud has accelerated the creation of closed feedback loop that is necessary for digital twin development. We expect the rate of this adoption to increase and digital twins to remain a critical component of digital transformation in various industries ranging from healthcare, manufacturing, and aerospace and defense to retail, consumer goods, and energy and utilities.

Consider an asset twin developed for an industrial machine to predict its health. After the IoT data are collected from the sensors presenting a snapshot of the state the machine is in, the simulation of this asset becomes the centerpiece of the digital twin. The health prediction capability would be of tremendous value in a system with limited resources where it is critical to find zero downtime maintenance plans. Another example is a supply chain digital twin that is built on supply, production, transportation, and inventory optimization models together with a stochastic supply chain network simulation to predict intervals of product shortages, understand what may cause these shortages, and identify the best courses of action to take to optimize cost and service under uncertainty. It is important to emphasize that neither of these digital twins is a one-off solution. Each matures over time and drives learning and adaptation because of which virtual models are improved and control in the physical world is enhanced. Since it is the only practical technology to model, understand, and optimize complex systems, simulation is the pivotal component of these digital twins. Empowered by simulation, digital twins drive decisions that unlock value in businesses.

In addition to simulation, building asset and process twins requires a variety of analytics tools ranging from IoT, statistical modeling, and visual analytics to AI/ML, natural language processing, computer vision, and optimization. However, at the heart of an asset twin often lies a physics-based simulation driven by domain expertise and data. At the foundation of a process digital twin, there is a flexible, data-driven, and scalable process simulation operating under uncertainty, mimicking the operations of the physical system through which thousands of objects may flow, and predicting the future KPIs. Complexity together with uncertainty often invalidates the use of deterministic techniques for developing decision-support solutions and turns stochastic simulation into a critical component of process twins. This tutorial brings clarity to what a digital twin is and discusses the role of stochastic simulations in the development of process twins.

The potential of digital twins has been discovered by the simulation community for some time now: the term "digital twin" has been mentioned in over 50 Winter Simulation Conference (WSC) papers in the last several years. Panels have been held to discuss what a digital twin is for manufacturing research and development (Shao et al. 2019) and how it relates to modeling and simulation (Taylor et al. 2021). Most applications discussed within the scope of digital twin development fall under the umbrella of Industry 4.0; see Shao et al. (2019), Sharotry et al. (2020), Flores et al. (2021), Lichtenstern and Florian Kerber (2022), and Biller (2023) for example studies. However, Ye et al. (2021) consider a healthcare system, Pu et al. (2021) focus on indoor modeling and mapping, and Pan et al. (2022) discuss smart city digital twins for public safety. Kulkarni et al. (2019), on the other hand, present an advanced tutorial on the use of digital twins for enterprise adaptation. More recently, Grieves (2022) discusses development and management of complex systems using intelligent digital twins and Biller and Biller (2023) focus on factory twin development. The authors further discuss how key digital twin functions and enabling technologies make it possible to describe, predict, and optimize factory KPIs including throughput, quality, cost, on-time delivery, sustainability, and resiliency. Focusing on the role of simulation augmented by AI/ML, Biller et al. (2022) and Biller and Biller (2023) outline several challenges that arise in digital twin use cases and describe how the simulation methodology research has enabled practitioners to overcome those challenges.

The goal of this tutorial is to share our understanding of what a digital twin is and our experience of digital twin development and deployment with the WSC community. We organize our presentation around answering the following questions:

- What are the digital twin required characteristics?
- What are the foundational elements of digital twin development?
- What are the key digital twin functions and which technologies does each function utilize?
- Are there digital twin development frameworks that could serve as guides for practitioners?

Sections 2 – 5 answer these questions. Section 6 discusses a supply chain digital twin use case and the role of simulation in its development. We conclude in Section 7 with an overview and a discussion of two aspects of twin development that are beyond scope but still important in the practice of twin development.

2 DIGITAL TWIN REQUIRED CHARACTERISTICS

Despite its enablement of digital transformation in a wide range of industry domains, the digital twin technology comes with challenges of adoption due to limited interoperability, market confusion, and heavy investment required in people and technology. The Digital Twin Consortium was founded in 2020 with the mission to bring multinational corporations, small and large technology innovators, academia, and governments together to collaboratively overcome these challenges and accelerate the development, adoption, and widespread use of the digital twin technology.

According to the Digital Twin Consortium, a digital twin is a virtual representation of real-world entities and processes, synchronized at a specified frequency and fidelity (Digital Twin Consortium 2020). Thus, a digital twin must have four main characteristics: (1) a physical representation; (2) a virtual representation; (3) synchronization between physical and digital representations at a pre-specified frequency and fidelity; and (4) ability to learn and adapt that leads to improved virtual models and enhancements in physical representations. We refer to these four characteristics as **D**igital **T**win **R**equired **C**haracteristics (DTRCs) in this tutorial. It is critical that DTRCs are used for a meaningful business outcome that can be clearly stated and objectively measured. Because of DTRCs 1 and 2, it is often asked whether any simulation model would qualify as a digital twin. A simulation model of a physical asset or process (DTRC 2) would by itself not be sufficient to meet the requirements of a digital twin. DTRCs 3 and 4 are what distinguish a traditionally one-off simulation model from a digital twin solution. Synchronization (DTRC 3) and learning (DTRC 4) are essential since digital twins evolve over the life cycles of products and processes. Ideally, they transform businesses by accelerating holistic understanding, optimal decision making, and effective controls. They build on a combination of real-time and historical data to represent past and present and predict future. Furthermore, digital twins are motivated by outcomes, tailored to use cases, powered by integration, and guided by domain knowledge.

3 FOUNDATIONAL ELEMENTS OF DIGITAL TWIN DEVELOPMENT

There are four foundational elements of digital twin development to meet the DTRCs: (1) data; (2) domain; (3) analytics; and (4) outcomes. If a simulation practitioner is asked about the differentiators of the digital twin under development, we recommend answering this question with respect to these four elements. We elaborate on each of these foundational elements in the remainder of this section.

3.1 The Data Element

This foundational element includes data of all types: engineering and design (product life cycle management (PLM)) data; experts' opinions; reliability reports; historical data from enterprise asset management (EAM), manufacturing execution system (MES) and enterprise resource planning (ERP); sensor IoT data; and historical and real-time data from texts, images, videos, and audio. It is important to know that these data sets would reflect the disruptions that occurred, and the real outcomes associated with the decisions implemented in previous time periods. Based on the use case on hand, different combinations of these data sets are used for describing the system's configuration and state and for capturing the uncertainty in the input processes. The granularity of the input data and the unit of time assumed by the digital twin are chosen to match the speed of making decisions. Within the context of factory twins, Biller and Biller (2021) discuss aligning data collection with the simulation models supporting decisions from strategic to tactical and operational. They describe the types of data needed to validate simulations and predict the factory KPIs. They further emphasize the importance of the simulation hot-start capability to support the (near) real-time operations optimization.

The collection of data is followed by a search for stochastic input-model characterizations that adequately capture the inputs' distributional characteristics. The representation of uncertainty in input processes (i.e., stochastic input modeling) is a problem that has been well studied by the simulation community. There are several tutorials presented at the WSCs over the years for representing, fitting, and generating multivariate time-series input processes ranging from being independent and identically distributed to having arbitrary marginal distributions and complex dependence structures (e.g., Pasupathy and Nagaraj 2015 and Law 2016). At the foundation of developing input models with arbitrary marginal distributions and dependence structures lies a transformation-based method that reduces the input-modeling problem to finding a suitable multivariate normal distribution. This distribution is chosen to match the distributional characteristics of the input processes whose dependence structures are captured by pair-wise correlations. In the case of using alternative measures of dependence, the approach becomes finding a suitable multivariate uniform distribution, i.e., a copula function (Biller and Corlu 2012). More recently, several researchers have investigated the use of neural networks to mimic the characteristics embedded in large simulation input datasets; see Wang et al. (2020) for an example study utilizing generative neural networks. While building on AI to automate input modeling to drive simulations with complex dependence structures is a novel idea, it is critical to have the ability to conduct sensitivity analysis and to account for the input model uncertainty in the presence of limited data (see Section 6.4 for a brief description of digital twin development and implementation challenges).

3.2 The Domain Element

The domain element combines subject matter expertise with physics-based modeling to build asset twins. A physics-based model captures the effects of governing laws of nature on operating the asset. If the asset were a pump and the objective were to predict its health, then motor current, pressure, and flow rate discharge would be among the primary model parameters to consider. Furthermore, there is a physical relationship among these parameters. Building a physics-based model accounting for that relationship would be the first step towards creating an asset twin. Integrating this model with data-driven analytics (i.e., a hybrid model) would be the next step to improve accuracy, lower cost, and scale the operationalization of the asset twin. Subject matter expertise also plays a critical role in process twin development. Often, production operations optimization projects require interdisciplinary teams whose expertise is critical to develop simulation models and understand constraints of performance optimization. Examples of domain expertise would extend to plant maintenance, material analysis, design limits, and operational constraints.

3.3 The Analytics Element

Developing digital twins requires an integrated use of advanced analytics tools ranging from IoT, sensor and streaming analytics (i.e., in-motion event analysis of real-world data generated from connected devices), and statistical modeling to computer vision, AI/ML, simulation, and optimization. A significant number of companies have been building on this integration in their digital twin development. Lockheed Martin maximizes uptime by using AI, IoT, and advanced analytics to predict when parts will fail, keeping more aircraft airborne for vital missions worldwide (Isbill 2022). US Gypsum – a world-wide industry leader in wallboard production – uses predictive analytics to estimate product quality for the line operators in real time (Reed 2022). Siemens combines plant simulation and IoT capabilities to improve production efficiency and quality by replaying history and conducting bottleneck and what-if analyses (Siemens 2020). The role of simulation is critical in the delivery of these outcomes. Furthermore, simulation complements composite AI – introduced by Gartner in 2021 – by bringing in the three key benefits of simulation: explainability, uncertainty quantification, and risk management.

Because simulation can be viewed as a big data generation program, performance prediction and scenario analyses can be accelerated by integrating simulation with machine learning and optimization. A code-based description of such an integration is available in Biller et al. (2019) within the context of clinical trial enrollment planning. Furthermore, simulation has been increasingly used as an environment to enable on-policy training of reinforcement learning agents (U.S. Patent and Trademark Office 2021). We refer the reader interested in reinforcement learning with discrete-event simulation to the review in Belsare et al. (2022) accompanied by discussions of application areas, challenges, and future work motivated by use cases.

3.4 The Outcome Element

All digital twins are expected to (1) provide situational awareness, thereby enable decision making with more information, and (2) automate the identification of the response to operate an asset and/or a process at their optimal settings. Examples of target outcomes include performance monitoring, data accuracy enhancement, increased turnover, decreased storage, increased production, cash and service improvement, and improved resilience. Nevertheless, this is not a comprehensive list. Isbill (2022) and Reed (2022) also report downtime reduction and product yield improvement. It is critical that digital twins are motivated by outcomes and tailored to use cases; the target outcome is the key driver in the design of digital twin solution.

4 KEY DIGITAL TWIN FUNCTIONS AND ENABLING TECHNOLOGIES

There are three primary functions to perform during the development of digital twins: (1) offline model development; (2) real-time synchronization; (3) online learning. Figure 1 illustrates these key functions for a supply chain digital twin. The offline model development represents the first phase of the digital twin development. Its output is a digital representation of the physical system, built and validated by using a static dataset representing the history of the system. The validated model is used to predict future KPIs and provide insights about how to optimize the system performance. Next comes the second phase of the digital twin development where the model is calibrated by using the most recent data reflecting the state of the system at that point in time. The calibrated model is used in the third phase where the capabilities of monitoring the system and tracking the past are in place. The future KPIs are predicted; actions to optimize performance are identified and implemented in the physical system to enhance control in real time. Thus, learnings obtained from this phase of the development are not just insights; they establish a closed loop between physical and digital representations. Next, we describe each of these three primary functions.

4.1 Offline Model Development

The offline model development function develops digital representations of processes by building on domain expertise, assumptions, and historical data. It further utilizes analytics techniques such as statistical and stochastic process modeling, AI/ML, simulation, and optimization. After the validation of the twin, the practitioner experiments with it via an integrated use of simulation and ML and derives insights about how to improve performance. However, the learning here is offline, i.e., no new datasets flow into the analysis.

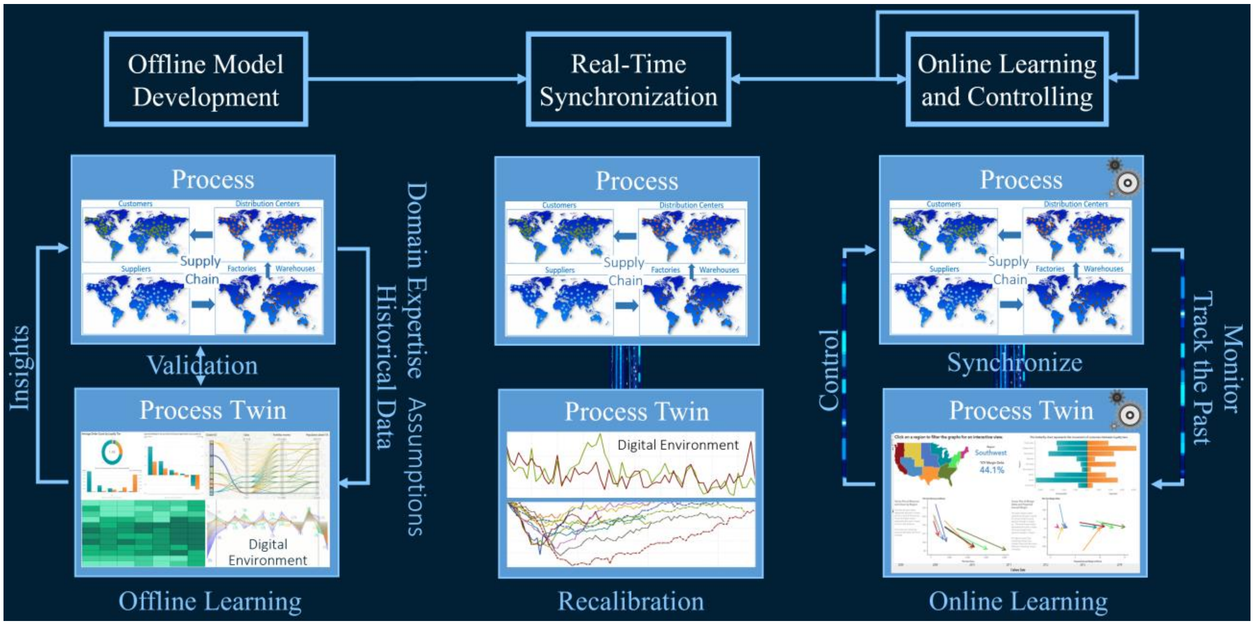

Figure 1: Digital twin development functions: Offline learning, synchronization, and online learning.

Traditionally, a one-off project falls under the umbrella of offline model development. If the virtual representation of the physical system is developed by using a stochastic simulation, then offline model creation overlaps with the development of a stochastic dynamic system simulation for which WSC offers tutorials. We refer the reader to White and Ingalls (2020) for the basics of simulation with focus on discrete-event simulation, Sargent (2020) for verification and validation, Sanchez et al. (2021) for the design of simulation experiments, and Eckman and Henderson (2018) for first ranking and then selecting the best among different courses of action that can be taken to improve performance. Biller et al. (2022) illustrates a cookbook recipe for a supply chain simulation project and describes how modular tasks come together for end-to-end offline learning. We further refer the reader to Sturrock (2020) for tips on simulation project excellence. However, it is important to recognize that the resulting solution would not yet qualify as a digital twin. What qualifies a solution as a digital twin is its online learning component enabled by the real-time synchronization function.

4.2 Real-Time Synchronization

A critical aspect of digital twin development is the synchronization of the real-world process and its twin via the use of streaming data in real time. Specifically, the IoT data collected from the sensors present a snapshot reflecting the system state at that point in time. The use of this data set to hot start the simulation is what primarily distinguishes a simulation developed as part of the digital twin effort from that created in a one-off simulation project. This distinguishing feature is evident in the hospital digital twin developed by Akbay et al. (2011), where the snapshots of the system are taken several times each day and fed into the model to hot start the supporting simulation with the current state of the hospital.

It is important to revise the previously developed stochastic models in Section 4.1 with the most recently collected historical data and combine them with experts' opinions when available. This can be done by integrating Bayesian methodology with simulation input modeling (Corlu et al. 2020). Additionally, real-time synchronization may require re-calibration of the simulation. This is especially important when the model includes parameters that are not fully known but still included in the model by relying on limited data and/or information. Morgan et al. (2022) describes the bias that may arise in the simulation outputs in such a case as input model bias and introduces a method that recalibrates the parameters of parametric input models to reduce the bias in the simulation outputs. It is critical to perform this re-calibration task on a periodic basis (Hua et al. 2022, Lugaresi et al. 2022, and Tan and Matta 2022).

4.3 Online Learning

The real-time synchronization is followed by online learning, which involves system monitoring and tracking the past, predicting the system performance and finding the best course of action to take via optimization. At this phase of the development, the digital twin is expected to provide enhanced visibility into the future and enable playing operational what-if games. Simulation plays the key role in equipping the digital twin with these capabilities.

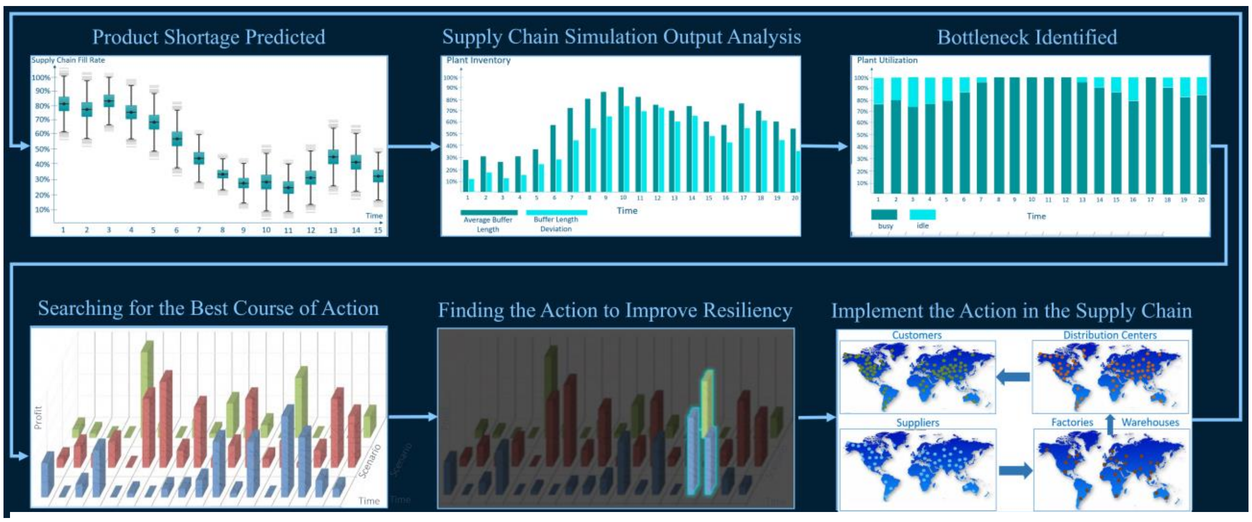

Figure 2: Online learning: Simulate – Predict – Optimize – Control.

Figure 2 illustrates an instance of learning from a supply chain digital twin. First, the supply chain network is simulated to predict intervals of product shortages (upper left plot). The distinction between the prediction capability in the offline model development and the prediction capability here is that the latter builds on hot starting the simulation with a calibrated model whose parameters and input risk profiles are updated with the most recent data at a specific frequency of synchronization. Then, the temporal study of the fill rate traces the source of the shortages to a manufacturing facility with high levels of inventory and utilization (upper right plots of Figure 2). This is followed by the investigation of the best course of action to take to address the capacity limitation in that facility. Ideally, the resulting solution not only maximizes the supply chain fill rate but also reduces the risk exposure. This action is next implemented in the physical supply chain, resulting in a closed feedback loop between physical and digital environments. The action itself – control – can be implemented either in an automated manner as a closed loop decision or in a manner augmented by human intervention and based on a decisioning logic.

5 TWO EXAMPLES OF DIGITAL TWIN DEVELOPMENT FRAMEWORKS

Market confusion arises as one of the challenges of implementing digital twins. There are limited use cases to learn from and little research on how to define requirements for minimally viable digital twins. Also, it is difficult to determine the technologies to use, ensure outcome delivery, and identify the knowledge and skills gaps to fill. A step towards addressing these difficulties is the use of a framework to facilitate collaboration in multidisciplinary teams tasked with digital twin creation. In this section, we present two examples of digital twin development frameworks that could be utilized for this purpose.

5.1 Digital Twin Cube

Figure 3 illustrates the digital twin cube introduced in the Digital Twin Insights Report (2020). It contains three main dimensions describing the concept of digital twins: life cycle phases, hierarchical levels, and most common uses. More specifically, each axis of the cube represents one dimension of the digital twin: The x-axis represents the six life cycle phases from design to decommission. The y-axis represents the six hierarchical levels from informational to multi-system. The z-axis represents the seven most common uses, one of which includes "simulate." Each combination of these three dimensions results in a different digital twin classification. Consequently, Figure 3 captures 252 different combinations in total. This is quite a simple framework; thus, it does not consider different input data types. Nevertheless, it is still an effective tool to particularly contribute to the initial digital twin development discussions.

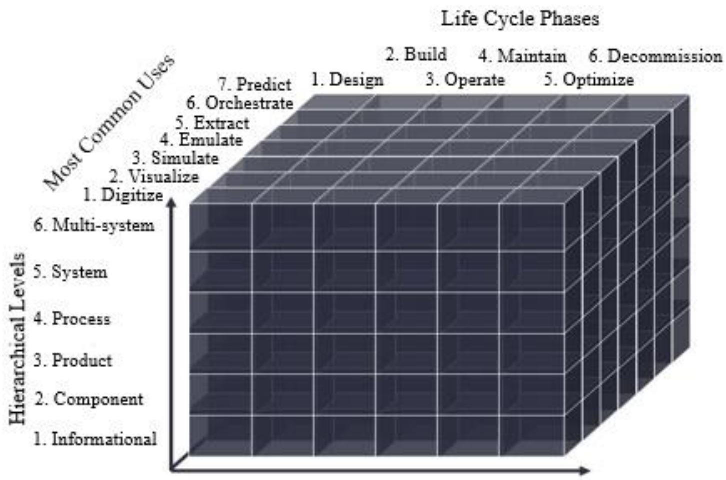

Figure 3: The Digital Twin Cube (Digital Twin Insights Report 2020).

5.2 Digital Twin Capabilities Periodic Table

Building on its 250+ members, the Digital Twin Consortium published the **D**igital **T**win **C**apabilities **P**eriodic **T**able (DTCPT) illustrated in Figure 4. DTCPT is an architecture and technology agnostic requirements definition framework aimed for organizations wanting to design, develop, deploy, and operate digital twins. It demonstrates the different ways in which the term "digital twin" can be interpreted. This tabulation of the digital twin capabilities uses six categories highlighted in different colors (Schalkwyk 2022): (1) "data services" connecting physical to virtual with the data collected from equipment sensors and control systems; (2) "integration" enabling digital twin communication; (3) "intelligence" representing the services associated with developing and deploying industrial digital twin solutions; (4) "user experience" interacting with digital twins and visualizing their data; (5) "management" representing ecosystem control; and (6) trustworthiness handling security, privacy, safety, reliability, and resilience. Each of these six categories is composed of capabilities with similar characteristics and applications. The main idea of DTCPT is to use these capabilities to meet the DTRCs introduced in Section 2 as a collection of a physical representation, a virtual representation, synchronization, and learning. However, every digital twin solution does not require the use of every capability in DTCPT. Although it is critical for a company on a journey of digital transformation to hit a high percentage of the boxes in Figure 4 by offering either core functionality or a solution together with third-party integration, this percentage would vary from one use case to another based on complexity and resource availability.

DTRCs and DTCPT apply to both asset twins and process twins. However, our tutorial focuses on process twins and discusses the role of simulation in process twin development. In DTCPT, simulation appears as a core functionality in two categories: data services and intelligence. The "data services" category includes the "simulation model repository" and "synthetic data generation" capabilities, while the "intelligence" category includes the "simulation" capability. This is because simulation can be viewed as a big system-data generation program, and it enables learning about physical assets and processes and making decisions with more information. Later in Section 6.3, we will present an alternative table of composable elements but customized to supply chains by building on the DTRCs (Section 2), the four foundational elements (Section 3), and our own experience of building supply chain digital twins with stochastic discrete-event simulations at the centerpiece.

6 A SUPPLY CHAIN DIGITAL TWIN USE CASE AND WHY SIMULATION IS CRITICAL

The digital twin use case of this section is accompanied by a development framework we have utilized and found useful in our digital twin projects. Our digital twin development framework, first version of which was introduced in Biller et al. (2022), builds on the DTRCs described in Section 2, the foundational digital twin elements introduced in Section 3, and the key digital twin functions and the digital twin enabling technologies presented in Section 4.

6.1 Description: A Supply Chain Digital Twin

The focus of this section is on supply chain digital twin development. Motivated by a consumer-goods use case, we consider the generic supply chain network flow illustrated in Figure 5 (Biller and Yi 2020). The target outcomes of the digital twin developed for this supply chain are three-fold: (1) to replay history; (2) to gain visibility into the future of the supply chain operations by predicting supply chain cost and service level; (3) to develop a playbook of decisions to implement to ensure good supply chain performance even when faced with disruptions. However, the development of a supply chain digital twin to meet these objectives is no easy task. It requires the collection of the right input data sets at a frequency that is in synch with the speed of decision making and the optimization of supply, production, inventory, and delivery (i.e., transportation) plans to be used for driving an end-to-end supply chain network simulation. Therefore, it is critical to ensure the design of the supply chain digital twin to build on the integrated use of various analytics techniques: **forecasting** to obtain demand forecasts; **optimization** to determine supply, production, inventory, and delivery plans; **simulation** to generate supply chain KPIs and quantify the risk in the KPI

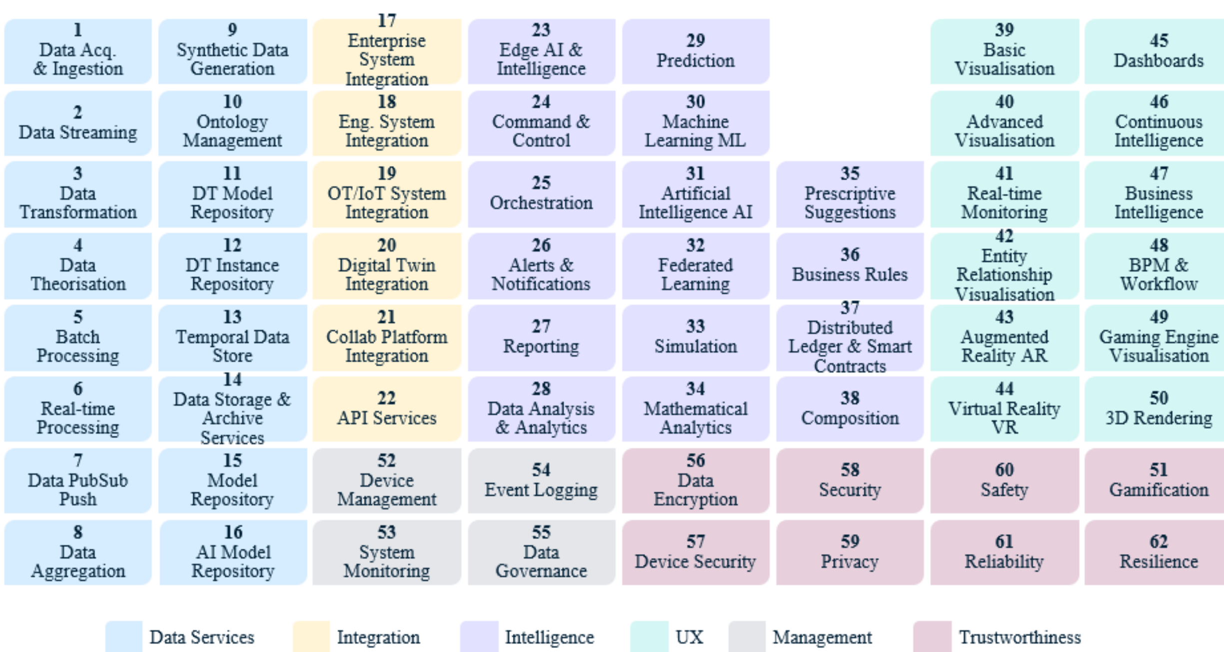

Figure 4: DTCPT (https://www.digitaltwinconsortium.org/initiatives/capabilities-periodic-table).

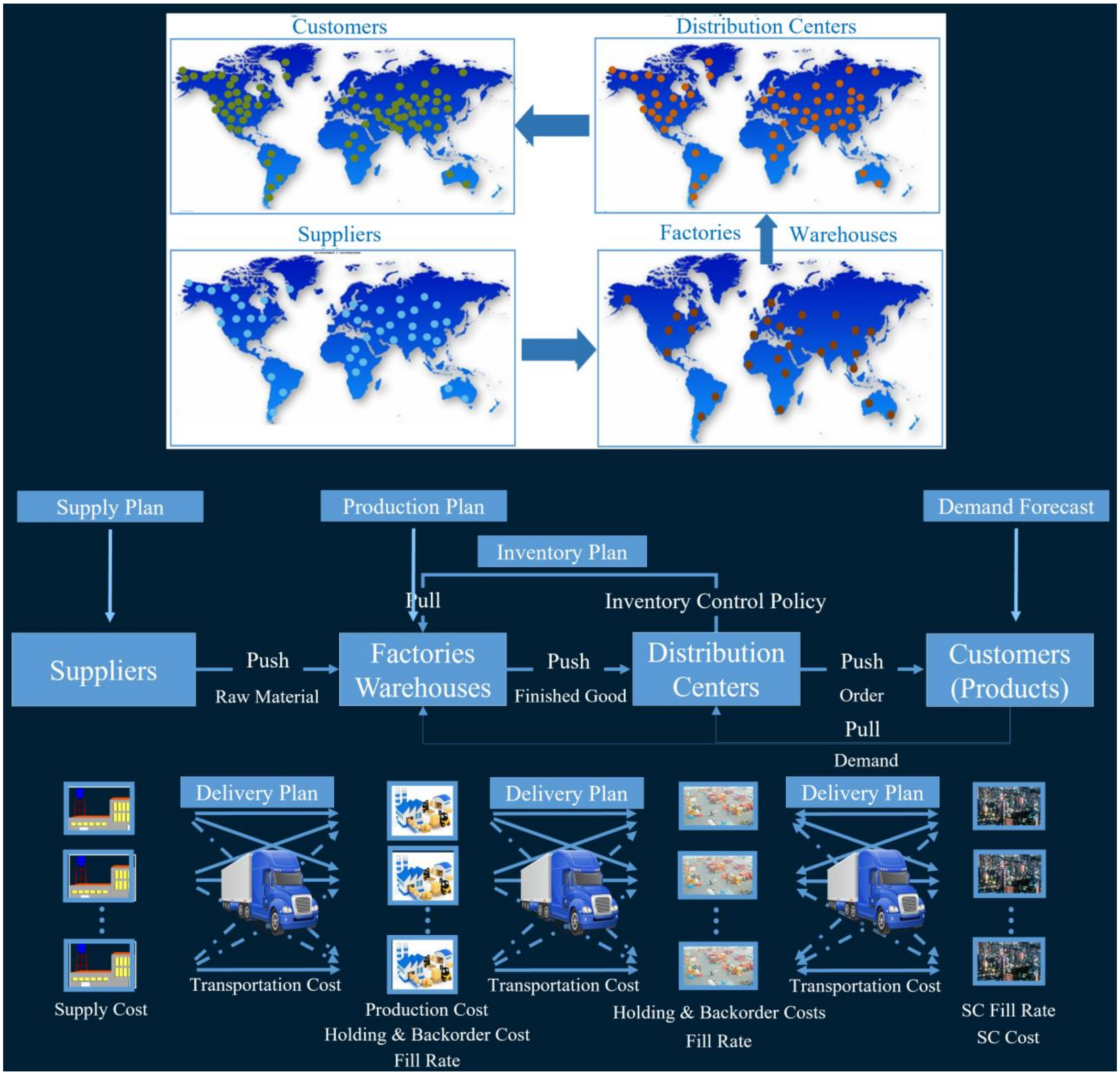

Figure 5: Illustration of a supply chain network with a map view and a network flow.

predictions; **simulation & optimization** to identify the corrective actions and manage the quantified risk; **AI/ML** to accelerate what-if games for real-time decisioning; and **data and visual analytics** to wrangle and analyze supply chain data and visualize the supply chain. In Section 6.2, we discuss the aspects of a supply chain solution to qualify it as a digital twin according to the consortium's definition introduced in Section 2. In Section 6.3, we represent the above list of advanced analytics techniques in the Analytics element of the supply chain twin development framework (Figure 6).

6.2 Revisiting the Digital Twin Definition

We ask whether the supply chain digital solution of this section has all the DTRCs introduced in Section 2: (1) The supply chain network is the physical representation. (2) Supply chain network simulation is the virtual representation. (3) Hot starting the simulation calibrated by updating the model parameters and the input risk profiles with the most recent data at a set frequency synchronizes physical and digital representations of the supply chain network. The frequency needs to be established based in part on the timeline of making decisions to achieve the desired outcomes and in part on the requirements of learning and adaptation. (4) Learning in the virtual world informs the management of the supply chain in the real world. The effects of the supply chain management decisions captured by the real outcomes together with the disruptions occurred, collected IoT data, and evolving assumptions and expert opinions are fed into the digital world in the form of new input data and/or an adapting supply chain business flow. This leads to a closed feedback loop between the physical supply chain and its digital twin. Thus, we conclude that our supply chain digital twin possesses all the DTRCs. It is important for simulation practitioners to ask the same question as part of their digital twin development effort and characterize 1) the physical representation, 2) the virtual representation, 3) the synchronization between physical and digital representations, and 4) the details of learning and adaptation over time. Doing so would clarify whether the supply chain solution is a digital twin solution.

6.3 A Supply Chain Digital Twin Framework

Figure 6 presents the framework that we find beneficial in our supply chain digital twin development. Every time a simulation practitioner attempts to build a new digital twin, she should not be developing it from scratch. Instead, she should modularize the development effort so that learning from one use case is transferred to the other, because of which development time is reduced, and scalability is attained.

With this goal in mind, we structure the supply chain digital twin development around the four foundational elements – domain, data, advanced analytics, and outcomes – introduced in Section 3. We assign several categories to each foundational element (see the leftmost column of Figure 6) and seven sub-categories to each category, placed horizontally to the right of the leftmost column. Additionally, we display the sub-categories required for developing the supply chain digital twin in black. Thus, Figure 6 can be viewed as the DTCPT for supply chains reflecting our first-hand experience in building supply chain twin solutions.

First, supply chain digital twin is identified as a type of process twin requiring a system modeling approach. Then, the development begins with the description of the supply chain flow logic, which is obtained by combining the supply chain network configuration with all necessary pieces of information and data that often include supply contracts and supplier data, initial inventory, production plan, customer demand, transportation details, inventory control policies, supply chain cost parameters, and characterization of disruptive events. Supply and production plans, details of transportation (i.e., delivery), and inventory control policies are generally obtained from solutions of deterministic optimization problems – possibly with different units of time – and brought together in the supply chain network simulation to predict how they will jointly perform in delivering high service levels with minimal costs. However, the details of data collection and definition are dependent on the types of decisions that the supply chain digital twin will support. For example, emergency maintenance decisions are typically made within minutes, while inventory adjustments might be considered every week or month (Biller and Biller 2023). They are further affected by the speed of making decisions. The "Frequency" category in Figure 6 refers to the data collection frequency to be aligned with the speed at which decisions are made. The "Description" category, on the other hand, indicates the potential sources from which the supply chain input data may be collected.

The next steps of development are (i) representing the uncertainty in the supply chain inputs, (ii) designing the experiments where the levers, which could be changed during a scenario analysis, are specified, and (iii) mimicking the flow of all entities through the supply chain network with a scalable, data-driven, and flexible dynamic supply chain network simulation. The analytics tools utilized for performing these steps are indicated as statistical modeling, visual analytics, optimization, simulation, and machine learning in the "Advanced Analytics" category of Figure 6. The execution of the simulation generates vast amounts of data representative of how the supply chain may perform in the future. By taking advantage of statistical modeling and visual analytics, the risk profile for the supply chain's service level is computed. The resulting supply chain digital twin can be used for several purposes. It can be used to predict KPIs and gain visibility into the future of supply chain operations. It can be used to assess the impact of decisions in

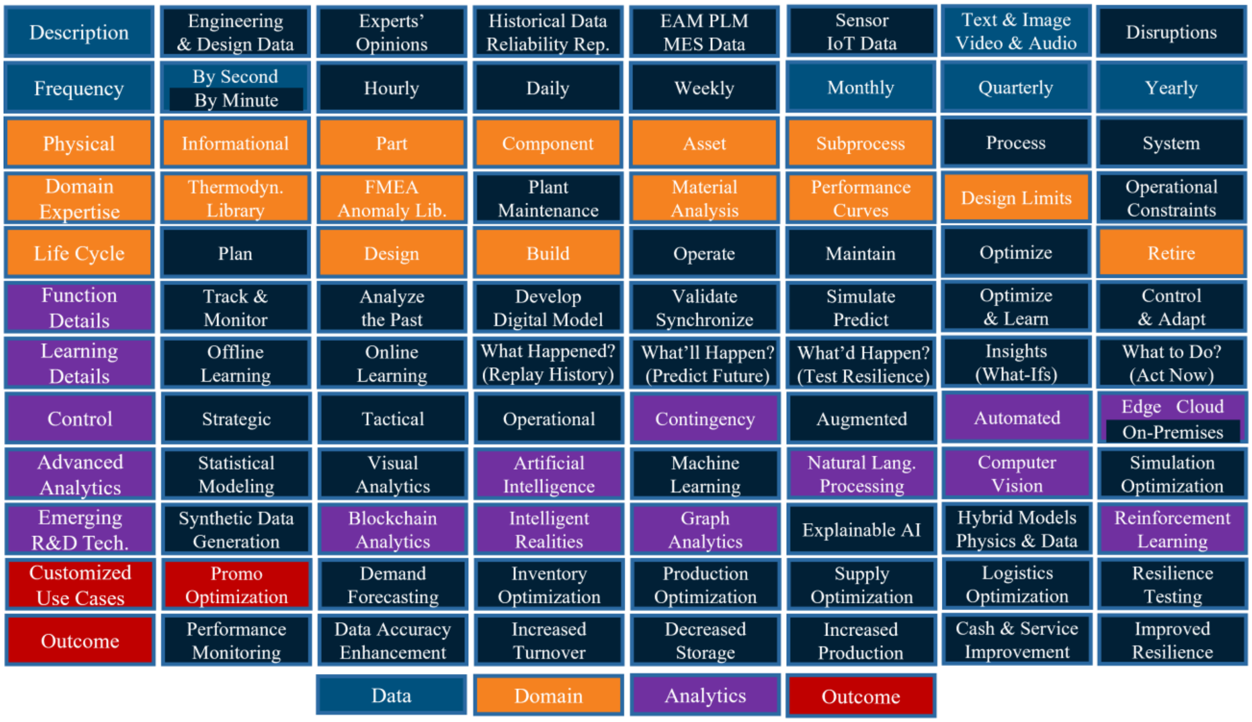

Figure 6: A supply chain digital twin development framework.

a virtual environment. The digital twin can be further used for stress-testing the supply chain. It is important to emphasize that the objective here would not be the prediction of the probabilities of disruptive events. The occurrence of these events is enforced within the simulation and the best courses of action to take – when confronted with these disruptions – are identified through an integrated use of simulation and optimization. We denote this capability of the supply chain digital twin as "Resilience Testing" in Figure 6. Furthermore, we summarize the digital twin development details discussed in Section 4 for generic process twins under the "Function Details" and "Learning Details" categories of Figure 6. The "Customized Use Cases" category is, on the other hand, specific to the problems that often arise in supply chain management. The framework ends with the outcomes that are often realized by supply chain digital twin solutions.

6.4 Challenges of Implementation

Despite all the benefits of the digital twin technology and its promise to help overcome many supply chain management difficulties, there are still challenges − both in development and in deployment − waiting to be addressed. In this section, we focus on the development challenges that may be overcome with the help of the simulation methodological work. Due to the limited space available in this tutorial, we provide an overview of our past work where those challenges are discussed, solutions are described, and references are provided.

We refer the reader to Biller et al. (2022) for the discussions of **synthetic data generation** with focus on Generative Adversarial Networks, **zone of confidence** capturing input parameter and model uncertainties in simulated KPIs, **fast sensitivity analysis** going beyond the use of global sensitivity measures with simulation, and **simulation and optimization** solving high-dimensional optimization problems under uncertainty. We refer the reader to Biller and Biller (2023) for the discussions of building data-driven **simulations from video, MES, and EAM data**, identifying factory **bottlenecks under input parameter uncertainty**, addressing **standardization and globalization in digital twin integration**, **accelerating what-if analysis** by integrating simulation with machine learning, and providing an environment to **train reinforcement learning agents for real-time optimization**. We further refer the reader interested in additional use cases to Biller et al. (2023) where the authors also discuss a use case on real-time queue monitoring and resource control as well as a use case on semiconductor manufacturing.

7 CONCLUSION

This tutorial describes how we envision the digital twins developed in industry. Specifically, we describe the digital twin required characteristics to help the readers better gauge when and how their simulation projects may qualify as simulation digital twins. We introduce the four foundational elements of digital twins and the three key digital twin development functions. We further illustrate the digital twin cube and the digital twin capabilities periodic table as two examples of digital twin frameworks. We conclude with a supply chain digital twin use case where simulation plays a key role.

We hope that this tutorial serves as a guide for readers wanting to learn what a digital twin is and beginning their digital twin development journey. While we have aimed for this tutorial to be a comprehensive introduction, there are two topics that we have treated as beyond scope. However, they are critical for successful twin development. The first topic is the use of computer-aided design (CAD) models and physics-based manufacturing simulations to optimize product design. This type of twin is alternatively known as "product twin" for which an example use case is provided by Anbalagan et al. (2021). The second topic that is beyond the scope of our tutorial is digital thread, which focuses on "how" the system is built (Szypulski and Garrett 2021). This tutorial focuses on digital twins representing real-world processes with benefits for end-users and customers. The digital thread, on the other hand, benefits developers by unlocking information silos and enabling traceability across domains. We recommend that the readers introduced to digital twins in this tutorial follow up on the digital thread topic.

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