Digital Twin: What It Is, Why Do It, Related Challenges, and Research Opportunities for Operations Research

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Digital Twin (DT), a new advanced digitalization paradigm, has attracted interest worldwide over the past five years. Practitioners and scholars alike still struggle with defining and realizing DT's possibilities in real-life scenarios. To resolve such confusion, we define the DT from an operations research (OR) perspective. We recognize that OR expertise plays a vital role in building an efficient and intelligent Digital Twin. We identify six promising research opportunities for the OR community that could expand the scope and depth of OR theory.

Key words: Digital Twin; simulation; digitalization

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1. Introduction

The concept of digital twin (DT) has attracted widespread interest for its ability to innovate the way of managing real-world entities and processes. The DT was strongly advocated as one of the "Top 10 Strategic Technology Trends" from 2017 to 2019 by the world's leading consulting firm Gartner (Panetta 2017, Panetta 2018, Panetta 2019). DTs of organizations are emerging to drive improved process efficiencies and new business opportunities (Panetta 2019). To operate efficiently and cost-effectively in the highly competitive and increasingly complex globalized economy, the European Commission also listed the DT for entire systems as one of the enabling technology for the value-centered industry (Müller 2020).

The DT concept was first introduced as the conceptual ideal for product lifecycle management (PLM) in a presentation given by Dr. Grieves in 2003 (Grieves 2006). The term DT was not used until 2011 (Grieves 2011) after two iterations of the concept development, namely mirrored spaces model in Grieves (2005) and information mirroring model in Grieves (2006). As the scope of the DT usage becomes broad, practitioners and researchers from various communities have spent the effort to reach a common understanding of the DT. The Digital Twin Consortium[1] has been established as the authority to orchestrate efforts from industry, government, and academia. The consortium released the official definition of the DT after an extensive review of documents and discussion between a cross-section of domain specialists.

Definition 1 (Digital twin, Olcott and Mullen 2020). A DT is a virtual representation of real-world entities and processes (hereafter EoP), synchronized at a specified frequency and fidelity:

- DT systems transform business by accelerating holistic understanding, optimal decision-making, and effective action.
- DTs use real-time and historical data to represent the past and present and simulate predicted futures.
- DTs are motivated by outcomes, tailored to use cases, powered by integration, built on data, guided by domain knowledge, and implemented information technology (IT) /operational technology (OT) systems.

The definition shows that the DT is not a new method or a piece of technology (Raghunathan 2019, EXOR 2020) but represents a new paradigm of advanced digitalization and automation (Minerva et al. 2020, Olcott and Mullen 2020). The paradigm is flexible to accommodate various practical use cases. In manufacturing, Siemens DT of a Vietnam-based automobile factory enabled the automobile manufacturer (factory) to master the manufacturing of ventilator at a monthly production capacity of 55,000 to alleviate the adverse impacts of the COVID-19 pandemic (Adams 2020). Unilever is working with Microsoft to develop the DT of the supply chain to digitally connect its 300 global plants step by step to satisfy their customers' needs of customization and on-demand products (Sokolowsky 2019). Other emerging application domains that pursue DT's ability of mirroring and managing real-world EoP include but limited to smart building (Khajavi et al. 2019), healthcare (Liu et al. 2019, Elayan et al. 2021), and smart city (Ruohomäki et al. 2018, Farsi et al. 2020).

Seeing the flourishing development of DTs, we express our thoughts on what role Operations Research (OR) academic community should take in the DT context. In particular, what is a DT from an OR perspective, how can DTs benefit from the OR's participation, how to benefit our own profession, and are we prepared to do so?

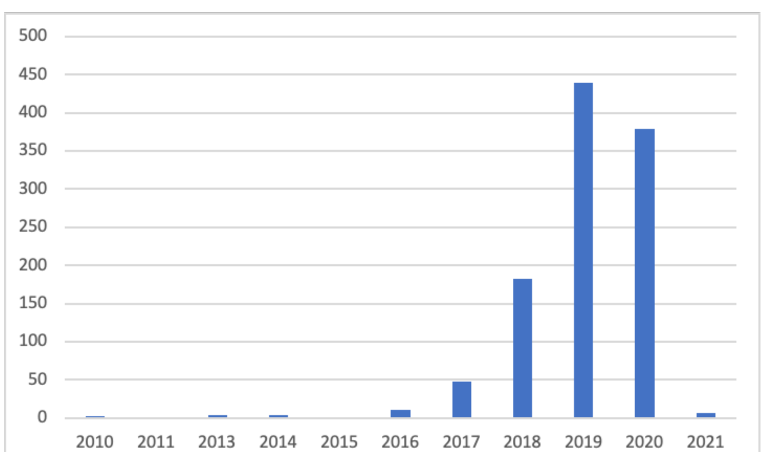
1.1. Motivation from industry and academia

We first demonstrate the timeliness of considering DT in our research agenda from the perspective of industry. NASA has used DTs to simulate complex spacecraft for decades. Due to the recent advances on the Internet of Things (IoT) and big data technologies, DTs are brought to the forefront for civil use. Industry is pursuing the DT concept enthusiastically to stay innovative and competitive. Many large software solution providers are among the pioneers of developing DT systems. Several startups have provided innovative and impressive DT solutions. There are more than 100 DT startups globally in Industry 4.0, logistics, and energy industry, according to a data science company's reports (StartUs Insights 2020b,a, 2019). Please see Appendix A for industry practices related to DT products and services. Meanwhile, the DT market has been expanding quickly. Research and Markets (2020) estimates that the total market size of the DT will be over \$100 billion by 2035, with an estimated annual growth rate of more than 20% for the next five to ten years.

Interestingly, many companies, startups in particular, advertise their DT solutions as "intelligent" features. For instance, a DT startup, Tunnelware, describes their products as "a DT of a tunnel construction system across its lifecycle, using real-time data to enable *understanding*, *learning* and *reasoning*"[2]. It is not surprising, since better decision-making is one key driver of digitalization initiatives in companies (Cognizant 2020). Due to tasks' increasing complexity and systems' deep interdependency, conventional simulation algorithms are expected to "evolve and spread" and then "form the basis of state-of-the-art DT" via a combination with optimization tools (Siemens 2020).

The wave of interest in the DT from industry has aroused scholarly attention. We searched publications whose titles contained the term "digital twin(s)" in the Web of Science Core Collection, accessed October 28, 2020. Irrelevant publications were excluded. The amount of research on the DT was plotted in Figure 1. While the paradigm's original concept was proposed almost 20 years ago, the related research has boomed only recently, possibly due to technological maturity level and market acceptance. Because designing and building a DT requires interdisciplinary efforts, diversified themes have arisen in the literature of DT, from its conceptual development to its industrial implementation, and from IoT technology to simulation techniques (see Jones et al. 2020 for a related summary).

Figure 1 Number of Publications Related to "digital twin" Worldwide from 2010, According to the Web of Science Core Collection.



OR is a discipline that deals with the application of advanced analytical methods to help make better decisions[3]. Concerning the abovementioned trend of advertising the "intelligent" features in the DT market, we would like to investigate the attention to the DT from our community. We searched publications whose content contained the term "digital twin(s)" in the INFORMS PubsOnline, accessed May 18, 2021. Martagan et al. (2021) developed a set of optimization models and decision support tools to improve biomanufacturing efficiency at MSD Animal Health in Boxmeer. They identified *the simulation model* as a DT of the facility. Review articles in operations management (OM) emphasized the DT's ability to generate real-time data and enable IoT-enabled operations (Mak 0, Olsen and Tomlin 2020). In particular, Olsen and Tomlin (2020) mentioned the real-time, data-rich, system-level optimization and data usage issues but did not discuss the challenges and research questions in detail. The understanding of the DT in Adner et al. (2019) is the closest one to this paper, where we identify the DT as a paradigm of advanced digitalization and automation. Adner et al. (2019) discuss the DT as a concrete example of modern digital transformation, whose core components include representation, connectivity, and aggregation.

In summary, several papers noted the growing interest in the DT and the DT's potential but did not evaluate the connections between the DT and the OR research in detail. We intend to fill the research gap and stimulate more thought in our community on expanding OR in the DT paradigm. The wide range of DT applications will allow our community to explore collaboratively with practitioners from different industries. Such extensive collaboration will push the boundaries of our expertise and increase our impacts than before.

2. An OR perspective on DT

Given the driving forces from industry and academia, it is imperative for our community to ponder how the connections between the DT and the OR discipline. We first discuss the terminology issue to relate the language used in the existing DT literature to an OR readership. Then we define the DT from an OR perspective. After that, we briefly discuss what can we contribute and how to benefit our own profession.

Terminology: We introduce the foundational elements introduced by Definition 1 and discuss what are the corresponding terms in our community. According to the consortium (Olcott and Mullen 2020), there are three foundational elements in the DT. The first is *the real world* that can refer not just to the EoP of interest but also the environment with which entities interact. The first element naturally lends itself to problem background in a common OR research. The second is the *virtual representation* that is a set of correlated digital models and supporting data. The consortium grouped digital models into two categories: (1) a representational model which consists of structured information which generally represents the states of entities or processes; (2) a computational simulation model which is an executable model of a process and consists of data and algorithms that input and output representational models. The most OR-related digital models can be mathematical formulations and simulation models. Other types of digital models include but not limited to: 3D meshes, 3D CAD Models, databases, and even Excel spreadsheets.

The third is the *mechanism* by which the virtual and real-world entities are synchronized, including observational mechanisms that mirror the real world in the virtualization and interventional mechanisms that mirror the virtualization in the real world. For the types of the mechanisms, observation mechanisms could include sensors, images, and videos; intervention mechanisms could include actuators, robots, and humans. From the perspective of OR research, observation mechanisms provide input data for solving problems. The DT system can provide both autonomous decisions and decision support (usually human-in-the-loop). It is a matter of different interventional mechanisms. For the frequency and fidelity of the mechanisms, the frequency of synchronization might vary (i.e. real-time, daily, milestone, etc.) and the fidelity (the degree of precision and accuracy applied to the virtual representation) can be tailored to the use cases, depending on how rapidly the real-world changes and what is the desired applications goals. That's to say, the decision-making in DTs is not necessarily real-time or short-term. A wide range of decision-making problems, from strategic to tactical and operational decisions, can be of interest in the DT. Moreover, what is the best frequency and fidelity is a critical OR-related problem in the DT as well.

What is a DT through our lens: Relating the foundational elements in the DT to the corresponding terms in the OR provides a sketch of the connections between the DT and the OR discipline. To enable a better understanding, we synthesize the properties that characterize an effective DT and propose Definition 2 from an OR perspective. Compared with Definition 1, the detailed requirements in Definition 2 are helpful to identify how the DT and the OR discipline benefit from each other.

Definition 2 (digital twin). From the lens of OR, a DT is a set of models and data that corresponds to a real-world EoP and

i. accurately and timely represents the EoP's characteristics, behavior, and reasoning in a target context with respect to all application goals;

ii. univocally identifies the EoP and enables inter-operability, composability, and integration with other DTs and the environment;
iii. supports holistic understanding, simulation of predicted futures, and optimal decision-making, especially in the absence of a procedural solution; and
iv. satisfies multidimensional needs (sharing of data and usage, implementability in modern software architectures, and adaptability to the changing environment).

What can we contribute: To implement a DT with properties (i)-(iv) in Definition 2, there is a series of interconnected decisions about the digital models, data, and synchronization mechanisms. Generally, the OR community can provide a modeling framework and decision-making methodologies to generate insightful guidelines and provide supporting tools. Specifically, we classify the related research into four themes, including building digital models, combining supporting data, solving problems in real-time, and managing DTs.

How to benefit our own profession: In each theme, we also discuss how the DT concept motivates interesting questions for us to advance OR research. Addressing the new challenges in DTs requires collaboration with researchers from information systems (IS), quality, statistics and reliability (QSR), AI, and data mining. Implementing an entire DT system will be far outside the expertise of the above research communities and require a broader range of cross-disciplinary work, including but not limited to software engineering (database management system in particular), augmented reality/virtual reality for visualization, and electronic engineering for communication and system control. Moreover, though the original concept was based on PLM in smart manufacturing and aerospace engineering (Grieves 2005, 2006, 2011, Glaessgen and Stargel 2012, Shafto et al. 2012), the specific application domain has lost emphasis. As the application scope continues to widen, collaborative work with a cross-section of domain specialists is required as well. Indeed, the multidisciplinary approach enables DTs to play a pivotal role in developing the smart industry and intelligent enterprise (Anasoft 2019). Seizing the significant cross-disciplinary opportunities probably expands our research scope and improves the visibility of the OR community in industry and academia in general.

3. DT Challenges and Research Opportunities for the OR Community

In this section, we would like to discuss several concrete research opportunities in each research theme proposed above. By discussing how can DTs benefit from OR, we identify the connection between existing OR approaches and DT challenges. By discussing how can OR benefit from DTs, we argue that new research questions in OR will be needed. Through the discussion, we do not attempt to delimit the scope of OR research in DT. Instead, we encourage the OR community to make contributions and exploit more research opportunities in building intelligent DTs and, meanwhile, benefit our profession.

3.1. Research theme 1: building digital models

Challenges: Real-world EoP are becoming complex. Traditionally, multiple models are used to represent and manage different business processes. For example, digital models for an industrial product through product lifecycle stages are still "only loosely interconnected today" (Siemens 2020). The DT seeks to represent and reflect the product state across the entity's entire lifecycle, from the design phase to production, operation, and disposal (Haag and Anderl 2018). The DT requires system-level digital models to build a comprehensive view for the EoP.

3.1.1. How can DTs benefit from OR?

According to Dyson et al. (0), OR typically involves the development and use of analytical methods and quantitative/mathematical models to improve organizational decision-making (we discuss the qualitative methods in OR in § 3.1.2). DTs require abstracting the complex system and focusing on a few relevant status and behaviors for specific applications, summarized as composability by Minerva et al. (2020). In our community, we discuss two types of quantitative approaches that have contributed to building digital models for specific applications in the DT: (1) mathematical formulations; (2) simulation models.

Mathematical formulations: Mathematical formulations (e.g., linear programming, mixed integer programming) breaks the whole system into related parts that are formulated in a mechanistic way (Smith and Shaw 2019). The formulations can significantly reduce the real-world EoP complexity and provide mature solutions for specific applications in DT systems. There are substantial works on how to formulate and model a specific problem. For example, Pillac et al. (2013) review the applications and methods of dynamic vehicle routing problems; Mula et al. (2006) discuss the models for production planning under uncertainty; integration of production planning and scheduling; Franco et al. (2021) study the modeling assumptions for human behaviors. Unfortunately, these models can only provide predefined solutions and fail to understand how this solution relates to the whole system (Smith and Shaw 2019).

Simulation models: Compared with mathematical formulations, simulation is more flexible to mirror and predict the behavior of complex EoP. Simulation has a broader research community than just OR. For example, the best-physics simulation models (the most accurate, physically realistic, and robust models) emphasized by NASA are mainly related to computer models in mechanical engineering. Currently, simulation models that represent the real-world EoP accurately in the DT context have mostly been developed in design and engineering (Siemens 2020). Simulation models in OR focus on industrial systems and business problems (Naylor and Finger 1967, Brailsford et al. 2019). Typical simulation methods include discrete-event simulation (Cassandras and Lafortune 2010, Li et al. 2016), agent-based simulation (Macal and North 2005, 2009, 2014), and system dynamics modeling (Sterman 2001). Hybrid simulation that combines two or more of the above methods has become popular to tackle complex business problems (see Brailsford et al. 2019 for a review on hybrid simulation modeling in OR). The participation of the OR simulation community in the DTs research will help extend DTs' representative capability from design (e.g., flying vehicle design discussed by Glaessgen and Stargel 2012) to operation (e.g., the predictive maintenance discussed by Tuegel et al. 2011, Mi et al. 2020) and even service (e.g.,the traffic environment simulation discussed by Zheng et al. 2020).

Data-driven calibration methods of simulation models allow the full use of historical data in DTs. Typically, simulation models in operation and service optimization usually involve simplified physical models that may be unable to precisely predict real systems' behavior due to some unobservable interdependency. To succeed in this regard, Birge (2012) discusses the particle methods for data-driven simulation and optimization. This method provides robust estimation and prediction for the distribution of an unknown state in a Markov process from noisy observations with general nonlinear transitions. Ruiz et al. (2018) develop the idea of learning to simulate and propose a reinforcement learning-based method to automatically estimate a simulation model's parameters. Instead of estimating a predefined function's parameters, recent studies propose methods to estimate the output directly. The method in Peng et al. (2020) estimates unknown parameters of a stochastic model by directly fit the underlying model to the output data, without assuming an analytical likelihood function. Zheng et al. (2020) extend the application of learning to simulate to estimating an agent's behavior directly, rather than calibrating a predefined driver policy's parameters. Their proposed method yields superior performance in recovering an individual vehicle's policy and its real trajectories.

3.1.2. How can OR benefit from DTs?

Given Property (iii) and (iv) in Definition 2, DTs seek to provide a system-level digital model that enables a holistic understanding and has the adaptability to the changing environment. Motivated by these requirements, we express our thoughts on two research opportunities in building digital models that OR might benefit from DTs: (1) mixed quantitative and qualitative modeling approaches; (2) automatically generating simulation models.

Mixed quantitative and qualitative modeling approaches: OR methods can be actually divided into two groups: quantitative (hard) OR and qualitative (soft) OR. Dyson et al. (0) argued that qualitative OR is a legitimate branch of OR and the authors identify the emergence of mixed soft and hard modeling. We find that the challenges facing by the DTs might drive the change from quantitative modeling to mixed quantitative and qualitative modeling approaches due to the following reasons.

First, the DT paradigm will be suitable for problems that cannot be solved by a procedural solution or in a functional way (Minerva et al. 2020). One important characteristic of qualitative OR is the usage in an ill-defined problem situation (Dyson et al. 0). In § 3.1.1, we discuss how well-developed quantitative models can be used to build digital models in the DT. In fact, quantitative approaches are better suited to "tame" problems that can be more easily formulated rather than "wicked" (e.g., ill-structured, complex, with swamp conditions) (Smith and Shaw 2019).

Second, DT requires the capability to "observe, analyze, and understand real-world interactions and impacts on different objects at a very granular level" (Minerva et al. 2020). Problem structuring methods (PSM) are a class of qualitative OR modeling approaches, which see problems as systems in which elements are connected by interrelationships (Smith and Shaw 2019). This bottom-up nature of qualitative modeling (Mingers and Rosenhead 2004) fits with the requirement of granular representations in the DT.

Third, qualitative modeling enables DT to provide holistic understanding, which is a key capability sought by the DT (Lacroix 2021). Smith and Shaw 2019 study the characteristics of PSM. The authors propose 13 questions that differentiate PSM from other methods, including methods to calculate an attribute of a system, methods to replicate or forecast system behavior (discrete event simulation), and optimization method (linear programming). The authors conclude that PSM seek to provide a holistic understanding of the system while other methods usually fail.

In solving wicked and complex problems, quantitative models still have an important role in reducing real-world complexity and supporting decision-making (Dyson et al. (0)). The use of qualitative methods also builds qualitative models (Smith and Shaw 2019). For example, Kotiadis and Mingers (2014) discuss the combination of PSM and simulation methods such as discrete-event simulation and system dynamics. The authors conclude that the combination enables a better understanding of the situation of interest and the situation to be expressed and structured. In summary, addressing the complex problems facing by the DT offers opportunities for collaboration between quantitative and qualitative modeling approaches.

Automatically generating simulation models: The DT needs adaptability to the changing requirement and environment. However, manually synchronizing simulation models is both time-consuming and error-prone (Reinhardt et al. 2019). Considering automatically generating simulators is important in the DT context. Bergmann and Strassburger (2010) summarize four challenges in automatic simulator generation. First, the data required from external systems can be incomplete. Second, capturing and describing complex behavior through algorithmic descriptions is difficult. Third, if the level of automation is limited, any details that are manually added by experts may be omitted when automatically generated elements change. Fourth, simulators can easily be discarded if they are incapable of learning and adapting.

The DT system enables automatic access to external data for automatic simulator generation. Reinhardt et al. (2019) survey data sources, data variability over time, and information retrieval for automatic simulator generation in discrete manufacturing. They classify data sources into seven types: computer-aided design (CAD) data, enterprise data, knowledge base, program code, sensor data, stochastic values, and user inputs. These data can be either static or dynamic over time. Fortunately, DT systems integrate multiple systems to obtain digital models of various kinds (e.g., business systems, engineering models, purpose-built knowledge graphs, other databases, IoT data, etc.), according to Olcott and Mullen (2021).

The automatic construction of a simulator's structure is an important yet challenging process. Wenzel et al. (2019) focus on structures' automatic composition for simulators in production and logistics systems. Structural variation is a major challenge in generating flexible and adaptable simulators automatically. Typical structural variations include modifications to a connection structure, components' emergence and disappearance, changes of component types, and dynamic changes of behavioral models. Wenzel et al. (2019) present a combinatory logic-based approach to automatically generate and adapt structure variations from a collection of prefabricated components. They conclude that designing a more structured way to describe and process components, their relationships, and control logic is important.

Currently, automatic simulator generations have been applied to production systems. Popovics et al. (2012) build an automatic simulator for a conveyor system. The system's topology and the control logic (variables and object relationships) are automatically extracted from programmable logic controllers (PLC) codes. System states and parameters are retrieved from a manufacturing execution system (MES). Following a similar approach, Pfeiffer et al. (2012) automatically build a discrete event simulation model for a large-scale material handling system. To meet the broader application scope of DTs, automatic simulator generation for the service industry and complex business processes is worth investigating.

Another important issue in automatic simulator generations concerns the importance of considering analysis and optimization compatibility in a simulator's design phase. As Fu (2002) noted, embedding gradient-based algorithms will be difficult if an unbiased direct gradient estimate is unavailable for general-purpose simulators. Therefore, it might be helpful to evaluate a simulator's complexity automatically as well during the generation process. As a reference, Popovics and Monostori (2016) develop two measurements to gauge a simulator's complexity. The first measurement assesses structural complexity, based on a simulator's amount of objects and their relationships. The second measurement assesses required computational and algorithmic efforts.

3.2. Research theme x: combining supporting data

Challenges:

Adner et al. (2019) study the core component underlying modern digital transformation. One of the components is data aggregation that enables the "ability to combine previously disjoint data (e.g., location, search query, and social network) to answer questions that were formerly impossible to address" (Adner et al. 2019). Some analogous terms include data fusion and data integration. There are discussions on the differences between these terms (see xxx). We find it not necessary to clearly distinguish the above terms in the DT context, since all of them can be useful and what actually creates the value in the DT is their most striking similarity of providing the ability to combine multiple sources of data.

3.2.1. How can DTs benefit from OR?

3.2.2. How can OR benefit from DTs?

3.3. Research theme x: solving problems in real-time

Challenges: Ideally, the virtual representations that match the real-world closely enough can be used to test different decisions and optimize the system. Unfortunately, running such a high-fidelity model is usually time consuming while the practical problems always face a tight computation budget. Developing algorithms that can solve real-time, data-rich, system-level optimization is a challenging yet important task in DTs (Olsen and Tomlin 2020).

3.3.1. How can DTs benefit from OR?

Finding optimal or near-optimal solutions in practical times is related to a long line of work in OR. Exact algorithms are hard to apply in the real-time setting because they always face the complexity of computing the optimal policy due to the "curse of dimensionality" as well as analytically evaluating the system performance measures due to the complexity and stochastic nature of the system (Vera and Banerjee 2021, Nelson 2010). Classical ways to solve problems at a large scale include the use of heuristics and myopic policies. Unfortunately, the heuristics are usually dedicated to special problems (Bertsimas et al. 2019) and myopic policy is globally optimal only in some special cases (for example, see Baucells and Sarin 2019 for a discussion about the decision situations and utility functions under which myopic strategy is globally optimal). The importance of addressing problems in real-time has led to a substantial research effort. We discuss four types of approaches in the OR literature that have contributed to solving problems in real-time in the DT: (1) shortening the running time of a computationally expensive model; (2) using multi-fidelity approaches; (3) improving the utilization of computational resources; (4) utilizing the offline effort in real-time decision-making.

Shortening the running time of a computationally expensive model: One way is to build a metamodel that approximates the model output from the input directly (Barton and Meckesheimer 2006, Kleijnen 2009, Staum 2009). The critical issue of metamodeling is designing simulation experiments to improve prediction accuracy (see some recent works in OR, Rosenbaum and Staum 2017, Salemi et al. 2019b,a). Researchers have also developed specific techniques to address high dimensionality and discrete optimization problems. For example, Xu et al. (2013) propose an adaptive hyperbox algorithm whose efficiency is less affected by the problem's dimension increase; Lu et al. (2020a) focus on applying kriging to high-dimensional simulators and the proposed method can handle inputs exceeding 10,000 dimensions. For the state-of-the-art methods in addressing computing discrete optimization problems, we refer the interested readers to Semelhago et al. (0).

Using multi-fidelity approaches: Though high-fidelity virtual representations are emphasized, DTs have the ability to provide different abstractions levels for specific capabilities and services (Minerva et al. 2020). Peherstorfer et al. (2018) classify multi-fidelity methods into three classes: adapting a low-fidelity model with information from a high-fidelity model, fusing low- and high-fidelity model outputs, and using a high-fidelity model selectively based on information from a low-fidelity model. For example, Rhodes-Leader et al. (2018) use multi-fidelity modeling for the aircraft recovery problem. The proposed method balances the need of using high-fidelity simulations for good estimates with the computational difficulties of large and complicated solution space and short computation time constraints. Multi-fidelity approaches are advocated as a future work direction in simulation optimization in Fu and Henderson (2017). The authors suggest using a collection of models in which simple models are used for global search and more granular models are built for local search.

Improving the utilization of computational resources: Zhou et al. (2021) integrate a state-of-the-art optimal budget allocation method (Chen and Lee 2011) in DTs to determine trade-offs between making enough runs for accurate estimates and computation time. In addition to computing budget allocation, we see great potential for leveraging the power of parallel computing environments in the DT context. We take the ranking and selection problem in parallel computing environments as an example. Luo et al. (2015) modify the traditional fully sequential procedures for multi-core personal computers and many-core servers. However, they also report that directly implementing sequential procedures in parallel computing environments leads to statistical issues. To overcome the inefficiency of directly applying traditional approaches, Zhong and Hong (2020) propose new "knockout-tournament" procedures in parallel computing environments. Since required sample sizes increase linearly with the number of alternatives, and the number of communications between processors is minimal, the proposed procedures are well suited for large-scale ranking and selection problems. Zhong et al. (0) consider how to speed up a fully sequential procedure in parallel computing environments by reducing the burden of frequent communications and coordination.

Utilizing the offline effort in real-time decision-making: Seeing that more and more researchers study how to reuse the simulation efforts to solve real-time problems (see Nelson 2016, Jiang et al. 2016, Ouyang and Nelson 2017), Hong and Jiang (2019) summarize these works to a unified framework called "offline simulation online application" (OSOA). OSOA treats a simulator as a data generator to train predictive models offline, and it directly uses predictive models for real-time decisions. The authors illustrate how to apply OSOA in three typical problems: estimation, ranking and selection, and simulation optimization. Jiang et al. (2020) apply OSOA to online portfolio risk monitoring by building a logistic regression model, based on data generated in offline simulation experiments. In a real-time vehicle routing problem, Ulmer et al. (2019) combine offline value function approximation with online rollout algorithms to obtain a high-quality and computationally tractable policy for real-time decision-making.

In particular, since training machine learning models can address some of the complexity offline (Bengio et al. 2021), there are great potentials for combing machine learning techniques and OR to address real-time issues. We refer the readers to informative review articles (Bengio et al. 2021, Gambella et al. 2021) on combining machine learning and OR. An example is a similar idea called "plan online learn offline" (POLO), proposed by Lowrey et al. (2018). Based on Markov decision process (MDP) models, the POLO develops a synergistic relationship between local trajectory optimization, global value function learning, and exploration of uncertain reward. Another noteworthy contribution from the simulation community in OR is the symbiotic simulation (SS). The SS system focuses on "decision making at the *operational* levels by making use of real- or near real-time data (generated by the physical system), and which is streamed subsequent to the development of the simulation model", according to Onggo et al. (2021). The SS research develops a valuable integrative framework that combines data acquisition module, data analytics model, scenario manager, optimization model, simulation model, and machine learning model (Onggo et al. 2018). According to Onggo et al. (2021), machine learning method can be used to learn from the historical data and adjust scenario manager, optimization model, and simulation model with real-time data which enables adaptability and prevents the system performance from deteriorating.

3.3.2. How can OR benefit from DT?

Given Property (i), (ii), and (iii) in Definition 2, DTs represent EoP's behavior and interaction with other DTs in a timely manner and support optimal decision-making. Motivated by these requirements, we express our thoughts on three research opportunities in solving problems in real-time that OR might benefit from DTs: (1) considering interaction between DTs; (2) leveraging historical and real-time data; (3) redefining "real-time".

Considering interaction between DTs: The application scope of the DT is enlarged and the interaction between DTs is nonnegligible. As mentioned in Minerva et al. (2020), the usage of a DT for a large system is typically the "prediction and simulation of the behavior of an aggregated set of DTs to understand, control, govern, and orchestrate the behavior of a complex system" and the DT system should have "the ability of grouping several objects into a composed one and then to observe and control the behavior of the composed object as well as the individual components". However, it is challenging to evaluate the EoP's behavior, reasoning, and interaction in real-time. For instance, Dovgan et al. (2019) study the real-time multiobjective optimization algorithm for discovering driving strategies. A particular challenge for the future study would be the consideration of real-life neighboring vehicles and unexpected events on a real route.

Leveraging historical and real-time data: DTs will deliver a much broader array of data. This encourages OR researchers to consider the feedback process and how to better leverage historical and real-time data. For instance, Mandelbaum et al. (2020) combines real-time locations of patients in the cancer center, electronic health records, and appointments log to learn the real service durations and punctuality. The proposed data-driven appointment scheduling reduces cost (waiting plus overtime) significantly. An online version of the data-driven problem, which is considered as future work by the authors, is challenging yet important task. The primary challenge of online problem is to make decisions with incrementally revealed information (Jaillet and Wagner 2010). The quality of online algorithms is mainly evaluated by comparing the performance of a strategy with an optimal strategy that is derived offline with complete information (competitive ratios). Let take the vehicle routing problem as an example. Jaillet and Wagner (2008) study the competitive ratios of simple online routing problems. In practice, reoptimization and rolling-horizon algorithms are more widely used. For the edge of optimization, Bertsimas et al. (2019) scale reoptimization and rolling-horizon algorithms to real-world applications with thousands of taxis and tens of thousands of customers. Unfortunately, the proposed algorithms still fall short of fully leveraging the historical and real-time data. In the extensions, the authors recommend that historical and real-time data can be used to forecast the demand and provide an online estimate of the travel times. They also suggest that solutions should be updated given the vehicles' actual moves.

Interestingly, DTs' requirement to use historical and real-time data and the future directions advocated by OR research converge. How to leverage historical and real-time data from the physical world (not only the experimental data) to better update the model to capture the features of the stochastic system and adapt to the changing environment is listed as an open problem in the discussion of OSOA framework (Hong and Jiang 2019). Peherstorfer et al. (2018) point out that an important challenge in multi-fidelity approaches is to "move beyond methods that focus exclusively on models, so that decision-makers can draw on a broader range of available information sources". However, "managing and analyzing the sheer volume of streaming data coming in from thousands of sources to make sense of it all in real-time" is of great challenge (Bain 2020). According to Daugherty et al. (2021), only 11% of executives interviewed estimate that 100% of the data collected from IoT devices and/or sensors in their organizations is fully utilized. Addressing this issue requires close collaboration between researchers from not only the OR community but also the INFORMS quality, statistics and reliability, AI, and data mining communities.

Redefining "real-time": According to Power (2011), "real-time" in practice always has some latency between (a) the real-world EoP changes, (b) the reflection of EoP change in data in one or more systems of record, and (c) the availability of the changed data to decision-makers (or algorithms). The above summary only considers the process from real-world to virtual representations. If the feedback process is taken into consideration, there is additional latency between (e) the availability of the decisions proposed by decision-makers or algorithms, (d) the implementation of the decision by an actuator or an operator, and (f) the actual EoP changes. According to Minerva et al. (2020), the synchronization between EoP and the virtual representations in DTs should be timely, in such a way that the time between EoP changes is negligible with respect to the need and intended usage of the digital models by applications or users. In other words, the EoP changes between (a) and (f) should be negligible or at least not in conflict with respect to the suggested decisions.

Generally, two strategies are applied to trigger the algorithms in real-time problems: time trigger strategy (e.g., making decisions every minute) and event trigger strategy (e.g., making decisions when a new demand arrives). In the time trigger state, the length of the decision-making period affects the complexity of computation, and responses to critical changes may be delayed. In event trigger strategy, the actual EoP may change to another state before the decisions with respect to the last state is available. Heemels et al. (2012) conduct a debate on time trigger (periodic) and event trigger in system control. One element missing in their consideration is the computation time of algorithms. The algorithm runtime prediction (see Hutter et al. 2014 for a review) might be helpful to adjust the strategy (e.g., the length of the decision-making period) dynamically. An open question is how to consider the computation time of algorithms and combine different trigger strategies to achieve the timely synchronization and response in practical context.

3.4. Research theme x: managing DTs

Challenges:

3.4.1. How can DTs benefit from OR?

3.4.2. How can OR benefit from DTs?

4. Path ahead

4.1. Technology roadmap of the DT

4.2. Standards development

Standards: Securing data acquisition and communication through proper standards and protocols is important (Wolf 2020). As an adage suggests, "Without standards, there can be no improvement." Unfortunately, most of the existing standards are unable to convert huge, diversified, fragmented, and unstructured data from various sources into a unified format (Adamenko et al. 2020). The urgent need for detailed standards is speeding up the process of establishing such standards. For example, the International Organization for Standardization (ISO) is currently developing standards for DT terminology and framework in manufacturing[4].

If a DT is built for a large systems, it is an efficient way to combine multiple smaller DTs into a single aggregated one (Minerva et al. 2020). The aggregation leads to a greatest challenge for setting communication standards and protocols between various DTs. As Lu et al. (2020b) noted, in the manufacturing domain, though communication protocols for a single production system have been discussed extensively, standards for production networks are scarce. Every DT must handle various information models with different data representations and relationships (Harper et al. 2019). For instance, data are product-centric when capturing the state and dynamics of the manufacturing domain, but data are process-centric in the supply chain management setting (Tao et al. 2017).

4.3. Comparisons with other analogous concepts.

In this subsection, we distinguish the concept of a DT from other analogous concepts to resolve possible confusion. To draw a clear distinction, an important question is what kind of problems make a DT the best choice? According to Grieves and Vickers (2017), what makes a DT different is the ability to deal with *unexpected* situation in *complex* systems. The DT paradigm is suitable for problems that cannot be solved by a procedural solution or in a functional way (Minerva et al. 2020). For example, stochastic control is efficient for inventory control in a factory while the DT paradigm enables ownership management and continuity of service throughout a product lifecycle in a complex supply chain for all stakeholders (Kelkar 2021). A typical scenario of using DTs is "the prediction and simulation of the behavior of an aggregated set of DTs in order to understand, control, govern, and orchestrate the behavior of a complex system", as described by Minerva et al. (2020). We list four analogous concepts and discuss the detailed differences, as follows:

- **Simulation:** Simulation is not equivalent to a DT since a DT is not a single model or piece of technology (Raghunathan 2019, EXOR 2020). Simulation has a broader research community than just OR. In mechanical engineering, computer models are built to simulate the characteristics and behaviors of artifacts, such as CAD/CAE models. The OR simulation community mainly focuses on computer models that represent a process or system over time given events' probabilities and decision policies, including discrete-event simulation, agent-based simulation, and system dynamics modeling. Simulation, in a broad sense, provides an important tool for virtual representations in DTs but not necessarily the only approach. Moreover, simulation alone, without proper synchronization mechanisms, is not enough to enable holistic understanding, optimal decision-making, and effective action in DTs. For more discussion on DTs and simulation in smart manufacturing, readers may refer to the survey article by Shao et al. (2019).
- **IoT:** "The rise of DTs coincides with the rise of the IoT", as stated W. Roy Schulte, distinguished vice president analyst at Gartner (Hippold 2019). So, what are the differences between the IoT and DTs? Tom Maurer, senior director of strategy at Siemens PLM Software, explained that the IoT works as a bridge to inform the digital world about real-time performance and information in the physical world, but the IoT is not necessarily the only approach to connectivity in a DT(Wasserman 2017). Gartner added that the DT decreases the IoT's complexity since a DT decouples a physical system and overcomes data-redundancy concerns (Hippold 2019). For more discussion of DTss and IoT, readers may also refer to the recent discussion articles by Minerva et al. (2020).
- **Digital Thread:** The Digital Twin Consortium defines the digital thread as a mechanism for correlating information across multiple dimensions of the virtual representation, where the dimensions include (but are not limited to) time or lifecycle stage (including design intent), kind-of-model, and configuration history; the mechanism generally relies on stable, consistent real-world identifiers (Turner 2021). The concept of a digital thread aims at "capturing data through the entirety of design, manufacturing, and delivery of a process", according to Andrews (2020). By definition, a "digital thread" emphasizes compiling data throughout a product's lifecycle or a whole business process. DTs create business

value cost-effectively only if communication is enabled via digital thread inside or between DTs (Turner 2021).

- **Cyber-Physical Systems (CPSs) and Cyber-Physical-Human Systems (CPHSs):** According to Lee (2008), CPSs integrate computation and physical processes. CPHSs, meanwhile, integrate humans into a system (Sowe et al. 2016). Compared to CPSs and CPHSs, a DT requires more realistic digital representations to mirror the physical world. As Tao et al. (2019) discussed, virtual models are more important to the DT a since they help DTs with intelligent decision-making, while sensors and actuators are considered core CPS elements to enable connectivity. Therefore, we conclude that a DT is a more developed and flexible paradigm than CPSs and CPHSs, and it can be applied with a broader range of methods and technologies in various domains.

4.4. Potential risks and costs

Implementations of DTs incur risks, such as technological reliability, cybersecurity, and data privacy. First, the major concern facing most practitioners is a risk of misrepresentation (Miskinis 2019). Ibrion et al. (2019) conclude, having analyzed cases from the aviation and marine industries, that this misrepresentation risk can result from unreliable sensors, model failures, and wrong decision models.

Second, Spătaru (2020) reports the increasing cyber risks, including an ever-increasing attack surface, cybercriminals' growing interest in industrial enterprise, an underestimation of general threat levels, a misunderstanding of specific threats, and a poor choice of protection options. For instance, in 2016, the Mirai botnet infected nearly 65,000 IoT devices within 20 hours, launching massive distributed denial-of-service (DDoS) attacks worldwide (Antonakakis et al. 2017). See Vishwakarma and Jain (2020) for a survey of the increased DDoS risk in IoT networks.

Third, risk and uncertainty persist around data ownership and privacy issues. An analysis of IoT data (Internet of business 2017) highlights a lack of clarity about who owns industrial data—whether vendors, customers, or both. Companies may face a risk of inadvertently signing lopsided agreements with IoT system vendors. Further, companies should carefully handle sensitive customer data, which are increasingly exposed to criminal threats (Fuller et al. 2020). The European Union's *General Data Protection Regulation* (GDPR) proposes regulations for personal data privacy and security. Particularly, these new regulations require data controllers (companies) to explain their data use to data subjects (customers) (European Union 2018). Due to data analytics' complexity, fully eliminating all such risks is challenging.

Costs are another major concern for DTs' implementation, alongside risks. West and Blackburn (2017) conduct a cost-constructive-model (COCOMO) analysis to roughly estimate the costs required to develop a DT for next-generation air dominance (NGAD) aircraft in the U.S. Air Force. Assuming a standard and mature development process, this software development is found to require approximately $1 trillion to $2 trillion (including labor costs, development costs, and general expenses) with 750 million to 1 billion source lines of code. Even if companies decide to use software services already developed on the market, rather than developing their own systems, they should carefully evaluate costs based on their implementation scale. For example, Microsoft Azure Digital Twin charges $1 per million messages[5].

5. Concluding Remarks

Endnotes

[1]The Digital Twin Consortium, accessed April 5, 2021, https://www.digitaltwinconsortium.org/index.html.

[2]TUNNELWARS, accessed May 21, 2021, https://www.tunnelware.io/.

[3]INFORMS, What is O.R.?, accessed April 5, 2021, https://www.informs.org/Explore/What-is-O.R.-Analytics/What-is-O.R./

[4]ISO/IEC AWI 5618, *Digital twin – Concepts and terminology*, under development, https://www.iso.org/standard/81442.html; ISO/DIS 23247-1, *Automation systems and integration – Digital Twin framework for manufacturing – Part 1: Overview and general principles*, under development, https://www.iso.org/standard/75066.html.

[5]Azure Digital Twins pricing, accessed January 13, 2021, https://azure.microsoft.com/en-us/pricing/details/digital-twins/.

Appendix A: A Summary of the Current Industrial Software Solutions or Services for Digital Twins

In this appendix, we summarize some exciting industrial Digital Twin solutions providers. The list in Table 1 is not exhaustive, but it includes both mature companies and startups to provide a comprehensive view of the current industrial applications. We identify:

- Organization: The solutions providers' names. Organizations are arranged in alphabetical order.
- Products: The name of the Digital Twin solutions or services. Both product types and names are included.
- Launch Time: The year when an organization launched its solution. If the year is not explicitly labeled alongside the products, we may (1) use the year associated with the earliest reports, news, or websites about Digital Twin solutions that we could find for this company, (2) use the year that the startup was founded, or (3) leave this field blank when we could not find any official information.
- Functions: The functions that the product provides. We divided these functions into four categories: (1) product design and development; (2) machine and equipment health monitoring/channel monitoring; (3) predictive analytics (predictive maintenance/demand forecasting and business planning); and (4) dynamic optimization.
- Industries: The industrial domain in which the solution can be applied.
- End-user type: We include two end-user types; *buyers* are users who apply Digital Twin products in practice, and *suppliers* are users who develop Digital Twin products.
- Positioning: How the organization positions their Digital Twin solutions or services within their production lines.

Table 1: Summary of Current Industrial Applications.

Organization	**Products**	**Launch Time**	**Functions**	**Industries**	**End-user**	**Positioning**
ABB Ltd	Software solution: PickMaster Twin	2019	1. Machine and equipment health monitoring; 2. Predictive maintenance	1. Industrial equipment: manufacturing, robots; 2. Buildings	Buyer	A key software component of Industry 4.0
Amazon AWS	Software solution: Ayla Connected Home	2019	1. Machine and equipment health monitoring	1. Buildings	Buyer	

Organization	Products	Launch Time	Functions	Industries	End-user	Positioning
ANSYS	Platform/ Analytic Tools: Ansys Twin Builder	2017	1. Machine and equipment health monitoring; 2. Predictive maintenance	1. Industrial equipment: manufacturing	Buyer	Simulation powered Digital Twin
Autodesk	Platform/ Service: Autodesk Forge platform	2018	1. Product design and development; 2. Machine and equipment health monitoring; 3. Predictive maintenance	1. Industrial equipment: manufacturing; 2. Buildings; 3. Healthcare	Buyer	Create intelligent, data-rich digital prototypes of physical assets
anyLogistix	Platform: anyLogistix (ALX)	2019	1. Channel monitoring; 2. Demand forecasting and inventory planning.	1. Supply chain	Buyer	
Bosch	Service: 1. Bosch IoT Hub; 2. Bosch IoT Things	2018	1. Machine and equipment health monitoring; 2. Predictive maintenance	1. Industrial equipment: Manufacturing	Buyer	
Cisco	Software solution: Cisco Validated Design	2019	1. Machine and equipment health monitoring; 2. Predictive maintenance	1. Industrial equipment: manufacturing	Buyer	
Dassault Systèmes	Platform/ Service: 1. 3DEXPERIENCE platform; 2. SIMULIA: The living heart project	2018	1. Machine and equipment health monitoring; 2. Predictive maintenance	1. Industrial equipment: manufacturing, robots; 2. Aerospace and Defense; 3. Healthcare	Buyer	
E2open	Software/ Service: E2open Harmony	2018	1. Channel monitoring; 2. Demand prediction and business planning; 3. Dynamic optimization	1. Supply chain	Buyer	Networked, Harmonized, Optimized, Live

Organization	Products	Launch Time	Functions	Industries	End-user	Positioning
General Electric	Platform/ Service: Predic Platform, Predix	2016	1. Machine and equipment health monitoring	1. Industrial equipment: manufacturing	Buyer	Asset-centric digital twins
IBM Corporation	Software solution/ Online Marketplace: 1. IBM Maximo; 2. IBM Digital Twin Exchange	2017	1. Machine and equipment health monitoring	1. Vehicles: automobiles; aircraft; railcars; 2. Industrial equipment: manufacturing; power generation and transmission; Processing; 3. Buildings: commercial Buildings; industrial facilities; hotels	Buyer and Supplier	Trending for IoT
Microsoft Corporation	Software solution: Azure Digital Twins	2018	1. Product design and development; 2. Machine and equipment health monitoring	1. Buildings: workplace; 2. Construction	Buyer	Next-generation IoT spatial intelligence solutions
Oracle Corporation	Software: Oracle IoT Digital Twin & Simulator	2017	1. Machine and equipment health monitoring	1. Industrial equipment: manufacturing	Buyer	IoT Application
PETRA Data Science	Platform/ Software: MAXTA	2020	1. Machine and equipment health monitoring; 2. Predictive maintenance; 3. Dynamic optimization	1. Industrial equipment: mining	Buyer	Keep the industry moving forward in these uncertain times!

Organization	Products	Launch Time	Functions	Industries	End-user	Positioning
PTC Inc	Platform/ Software solution: 1. ThingWorx Industrial IoT Solutions Platform; 2. CREO; 3. Windchill; 4. Arbortext		1. Product design and development; 2. Machine and equipment health monitoring; 3. Predictive maintenance	1. Industrial equipment: manufacturing; 2. Products as Service	Buyer and Supplier	
QiO Technologies	Platform/ Software: QiO Foresight Platform	2015 (Founded)	1. Machine and equipment health monitoring; 2. Predictive maintenance	1. Industrial equipment: manufacturing; energy	Buyer	Fully automate AI model management
SAP SE	Software solution: 1. Digital Supply Chain; 2. SAP Predictive Engineering Insights enabled by ANSYS	2018	1. Product design and development; 2. Machine and equipment health monitoring; 3. Predictive maintenance; 4. Dynamic optimization	1. Industrial equipment: manufacturing; energy; 2. Automotive and Transportation; 3. Retail and Consumer Goods	Buyer	Intelligent technologies for the digital supply chain
Siemens AG	Platform/ Service: 1. MindSphere; 2. Tecnomatix; 3. Simcenter	2017	1. Product design and development; 2. Machine and equipment health monitoring; 3. Predictive maintenance; 4. Dynamic optimization	1. Industrial equipment: manufacturing; energy; 2. Vehicles: railcars; 3. Buildings: commercial buildings; industrial facilities	Buyer and Supplier	Shaping digitization
Swim	Software solution: swim continuum	2017	1. Machine and equipment health monitoring; 2. Predictive maintenance; 3. Dynamic optimization	1. Industrial equipment; 2. Transportation	Buyer	Digital twins and machine learning make for a potent pairing.

Organization	Products	Launch Time	Functions	Industries	End-user	Positioning
Visualiz	Platform: Visualiz	2017 (Founded)	1. Product design and development; 2. Machine and equipment health monitoring	1. Industrial equipment: energy	Buyer	a realistic VR/AR visualization platform that unifies your data sources into a digital twin

Appendix B: A Summary of Digital Twin Applications in the Literature.

In this appendix, we list Digital Twin applications in the literature. We do not intend to provide an exhaustive summary in Table 2. By providing some representative research, we hope to elucidate how researchers have contributed to Digital Twin applications. We identify:

- Reference: The citation of the research article.
- Domain: The domain of the problem to which the research applies Digital Twin.
- Functions: The functions of the proposed Digital Twin.
- Enabling Technologies: The hardware/software technologies and/or analytics used.
- Types: The types of research results.
- Application Scenario: Where the proposed research result is applied. We leave this field blank if an article explicitly mentions no scenario.

Table 2: Summary of Digital Twin Applications in the Literature.

References	Domain	Functions	Enabling Technologies	Types	Application Scenario
Tuegel et al. (2011)	Manufacturing: air vehicles, aerospace engineering	Reengineering aircraft structural life prediction	An ultrahigh fidelity model of individual aircraft, including multiphysics, multi-scale damage modeling; integration of structural finite element model and damage models; uncertainty quantification, modeling, and control; manipulation of large, shared databases, high-resolution structural analysis capability	Conceptual framework	United States Air Force
Cerrone et al. (2014)	Manufacturing: air vehicles, aerospace engineering	Structural life management	Individual component as-manufactured geometry modeling and simulation	Conceptual framework; simulation models	

References	Domain	Functions	Enabling Technologies	Types	Application Scenario
Söderberg et al. (2017)	Manufacturing	Geometry assurance (design, pre-production, production)	Locating scheme optimization; statistical variation simulation; inspection preparation; virtual trimming; joining sequence optimization; root cause analysis	Conceptual framework	
Brenner and Hummel (2017)	Manufacturing: learning factory	Shopfloor management	Indoor localization; scenario-live-simulations	Software application	University laboratory
Uhlemann et al. (2017)	Manufacturing: learning factory	Production system monitoring, process optimization	Multi-model real-time acquisition; simulation-based data processing	Conceptual framework	Conceptual learning factory
Zhou et al. (2020)	Manufacturing	Process planning, production scheduling, process analysis and regulation	Knowledge-driven digital twin manufacturing cell: high-fidelity simulation model, dynamic knowledge bases, knowledge-based intelligent skills	Conceptual framework; test application on a platform	University laboratory
Ivanov and Dolgui (2019)	Supply chain management	Risk management	Disruption scenario and recovery simulation; SC design optimization	Conceptual framework	
Greif T (2020)	Supply chain management	Construction site logistics optimization	Lightweight digital twin for non-high-tech industries: fill level monitoring	Decision support system	Building material supplier
Marmolejo-Saucedo (2020)	Supply chain management	Inventory and replenishment optimization	Facility location models, MILP solver, dynamic simulation, what-if multi-scenario analysis	Tools based on existing software	A pharmaceutical company
Park et al. (2020)	Supply chain management	Production planning for make-to-order supply chain	Distributed simulation	Conceptual framework	Automobile manufacturing SC

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