

Barriers to Implementing Digital Twin Technologies in Industrial Settings

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Abstract – Recent review articles highlight an exponential rise in publications on Digital Twin (DT) technology. Despite its recognised potential, DTs have yet to achieve widespread practical use. Following a presentation of the state of the art and an original conceptual diagram illustrating the technology, this work presents the key factors contributing to the gap between conception and implementation. Using experimental data from a laboratory water system and a reliability-based perspective, this analysis examines the practical limitations of DT application. The findings indicate that broader use of DTs depends on the technological maturity and reliability of all system components, which still require further development.
Keywords – Industry, Reliability, Flow System

I. INTRODUCTION

Michael Grieves introduced the concept of Digital Twin (DT) technology in 2002 during a presentation on industrial product lifecycle management [1, 2]. This concept extends earlier work on model-based adaptive control and state observers [1]. Today, DT technology evolves rapidly and ranks among the most strategically important trends [3]. However, these trends rarely translate into practical applications. In this study, we aim to identify the barriers, drawing on both a literature review and our own observations.

II. PROPERTIES OF DIGITAL TWIN TECHNOLOGY

A. Components

Fig. 1 illustrates the DT concept. This approach creates a Virtual Model (VM), aka Digital Entity, of a Physical Asset (PA), aka Target Entity. This model enables real-time simulation and monitoring [2, 4, 5]. The VM synchronises with the PA and optimises its operation. The PA adjusts dynamically based on direct instructions from the VM [2]. Actions performed on the VM generate observations that support decision-making and influence the PA [6]. The model must maintain sufficient accuracy for the

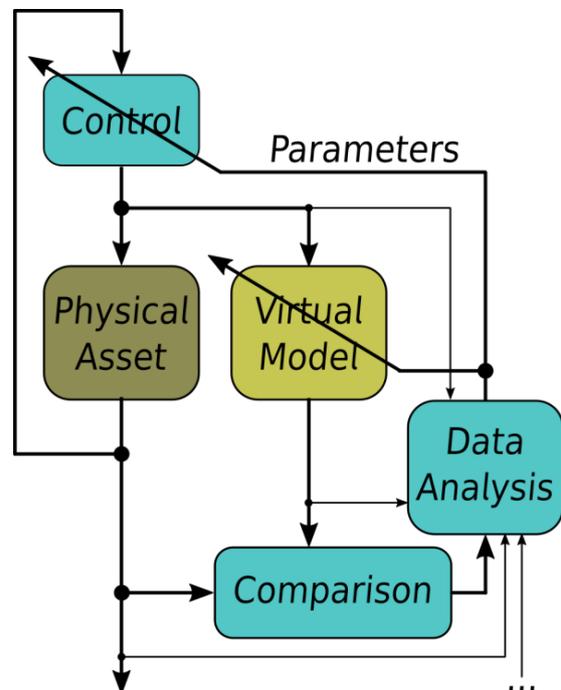


Fig. 1. Diagram of data flow in Digital Twins technology.

intended task.

DT system also includes several key components: data analysis, computing, real-time communication, large-scale data processing, and servicing functions such as quality control and prediction [1, 3]. In essence, the system compares outputs from the VM and PA, integrates all available data, and calculates control parameters for the PA. In Fig. 1, bold arrows represent the main flow of information. In DT technology, data analysis leverages all available information (depicted with thin arrows) to fine-tune both the VM and the control parameters.

Although DT systems may appear autonomous, humans typically remain involved in decision-making or intervention [6]. If the VM does not affect the physical

world, the system is referred to as a Digital Shadow [1, 7]. In some cases, systems only collect raw data throughout their lifecycle without real-time modelling. This approach is known as the Digital Thread [7].

A similar concept appears in virtual, aka soft or software, measurements. Here, a model replicates a real measurement process. It replaces physical instruments by using available signals to simulate measurements. However, this model does not influence PA [6].

Measurements play an important role in the diagram presented in Fig. 1. These measurements capture most of the input and output data from PA [6]. Without them, constructing an appropriate model would not be possible. The system must acquire data with low communication latency and maintain synchronisation. This task becomes particularly challenging when PA is geographically distributed [1].

The data collection process must operate quickly enough to track the asset's behaviour in real time. At the same time, the algorithms must update the model promptly to detect and respond to significant changes [6]. For the correct operation of the DT system, live data from the physical system must be continuously available. Therefore, communication and coordination must be reliable and efficient [1].

B. Applications

The literature shows that DT technology was first implemented in the aerospace sector, particularly in aircraft and rocket systems. Its use has since expanded to a wide range of domains, including manufacturing, industrial systems, urban infrastructure, and military operations [1, 8, 9], as well as medicine, energy, healthcare, and agriculture [1, 3]. Nearly half of the existing publications focus on manufacturing, covering both production- and product-oriented applications [3].

Researchers have also explored the use of DTs to support operations in measurement laboratories [6]. In addition, DTs are emerging as a promising tool for intelligent power systems [1]. Owing to the strong correlation between the physical asset and its virtual counterpart, DTs offer effective solutions to complex industrial challenges [9].

Although the literature on DT is rapidly expanding, most applications remain at the conceptual stage [1]. There is still a lack of comprehensive and high-fidelity digital models, such as those representing the entire human body [3].

Information and communication technology includes cyber-physical systems (CPS), the Internet of Services, and cloud computing [2]. Within CPS, DT technology plays a key role due to its ability to capture, predict, and visualise both real and virtual states of human-system interactions. It also facilitates autonomous operation [1, 5]. However, CPS are inherently complex. As complexity increases, their vulnerability to faults and failures also rises [10].

DT technology plays a significant role in Industry 4.0. Its implementation enables faster identification of physical issues and contributes to the production of higher-quality products [11]. DT is also regarded as a key technology in the 5th industrial revolution. This new industrial paradigm integrates advanced sensors and the Internet of Things (IoT) to promote collaboration between humans and robots. It emphasises a human-centred perspective in the design and implementation of technological processes [7]. At the same time, reliability remains a key indicator of the operability and performance of production plants within manufacturing systems [10].

DT helps reduce time-to-market and optimises both plant equipment and product performance [11]. It also enables predictive maintenance, which significantly lowers the costs associated with production system failures. Moreover, it supports optimal utilisation of production resources and enhances operational safety [4].

Introduced in 2020, a policy document promoting DT development in China has significantly influenced both economic and social progress. The initiative supports the advancement of modelling, simulation, data fusion, and related technologies [9].

C. Design

The design of DT systems typically involves several key phases. It begins with the Modelling Phase, during which multiple models are developed and evaluated. This is followed by the Simulation Phase, where the DT simulates the behaviour of the real system. In the Deployment Phase, the system is installed in its target environment. The Monitoring Phase involves using the DT to track the system's performance in real time. Finally, the Optimisation Phase focuses on enhancing safety, efficiency, and overall effectiveness [7].

D. Model

The VM enables engineers to perform prognostics, optimisation, and control within a digital environment [3]. It also facilitates real-time monitoring and optimisation of PA. By creating a virtual replica, engineers can test and refine the system before physical implementation, thereby improving safety—particularly in applications such as robotic systems—by conducting trials in a virtual environment [7].

The VM serves as a comprehensive and autonomous digital mirror of the PA. It maintains an interactive connection with the physical system through simulation, verification, prediction, and control across the entire lifecycle of the process. It leverages both historical and real-time data to support decision-making. DT technology represents a dynamic process [9], driven by advanced communication and computational capabilities [1].

The DT model can be described across four key dimensions: geometry (including shape and assembly), physics (encompassing properties, characteristics, and

constraints), behaviour (capturing system dynamics), and rules (which apply historical data to enhance model intelligence). Developing such a model requires interdisciplinary expertise [3].

DT technology integrates all available data to support simulation through multidisciplinary, multiphysical, multiscale, and multiprobability approaches. This integration relies on physical models, real-time sensor data, and operational history to ensure accuracy and adaptability [11].

The design of a DT model can follow various methodological approaches, including white-box, grey-box, and black-box modelling techniques [1]. Advanced modelling often demands significant computational resources. These computations can be performed either in the cloud or at the edge. Edge computing offers advantages such as reduced latency and lower data transmission volumes. However, it also presents increased vulnerability to cyberattacks [1].

The PA typically evolves over time, which necessitates continuous updates to the model parameters to maintain accuracy [6]. Achieving sufficient model fidelity is essential, particularly when we need the real-time predictions and responses. Model reduction techniques enable faster response times and more efficient tuning, meeting these demands [1].

Standard practices such as validation, verification, and accreditation can further enhance model accuracy [1]. In particular, model verification plays a critical role in ensuring that the model meets the required performance and reliability standards [3].

E. DT in water pipe systems

Water systems consist of reservoirs, pumps, pipelines with valves, flow meters, and outlets. Both industries and households rely on them extensively [9]. These systems either supply drinking water or support industrial operations. Depending on the application, they may stabilize water pressure at a target level or control the flow rate.

In pump applications, DT technology enables continuous anomaly detection and monitoring of pump operations. They support maintenance by providing real-time insights into system behaviour. These models help analyse failures, assess performance, and identify optimization opportunities. By improving failure prediction and mitigation, DTs enhance system availability and reduce project costs [9].

Another application involves a model of a university laboratory flow system. In this case, 2D or 3D computational fluid dynamics proved suitable for simulating two-phase flows during pipeline filling and emptying procedures. The success was attributed to a relatively simple installation and the use of advanced modelling techniques [12].

DTs also show promise in improving water consumption

forecasting. However, the sector currently lacks a unified framework capable of integrating advanced mathematical algorithms seamlessly and effectively [13].

III. BARIERS IN REAL APPLICATIONS

DT implementation presents several challenges, as mentioned in the literature. However, despite the growing number of publications on the topic, many authors tend to focus on the benefits while giving limited attention to the potential drawbacks of this emerging solution. These limitations include ensuring data security, integrating with existing processes, managing high initial investment costs, and addressing the skills gap, as operation and maintenance require well-trained personnel. Additional barriers include the lack of standardisation, ethical concerns such as potential job displacement, and resistance to change among employees [7].

Despite growing interest, most DT implementations remain application-specific and isolated, limiting their transferability across projects. Looking ahead, proprietary data regulations may further restrict data availability. Furthermore, the high data transmission rates required by DT systems contribute to increased energy consumption, raising concerns about long-term sustainability [1].

The above-presented properties of DT systems reveal a set of conflicting requirements. A DT performs effectively when it remains simple. However, we also expect it to deliver benefits in complex systems. Such demands frequently drive up system complexity, making it difficult to control costs and maintain efficient operation.

Another major limitation lies in modelling accuracy. High accuracy requires the inclusion of a large number of details, which is only feasible for relatively simple tasks. When modelling more complex processes, the number of input signals and the required computational power increase significantly. To address this, behaviour-based models—such as grey-box or black-box approaches—are often employed. However, these models may introduce substantial approximation errors.

An illustrative example is the modelling of a laboratory water flow system. In this setup, a pump drives the flow in a closed-loop system, controlled by an inverter. Several flowmeters measure the flow rate. Both the pump and flowmeters use digital communication protocols, enabling control of the inverter frequency and acquisition of flow rates. A PC manages the entire system, allowing for repeatable experiments.

Fig. 2 illustrates the flow rate dynamics in response to variations in inverter frequency. The system exhibits distinct time responses due to the combined effects of software, electronics, motors, fluid dynamics, and materials properties. Understanding the root causes of these variations would require considerable time and effort.

One possible approach is to explore correlations

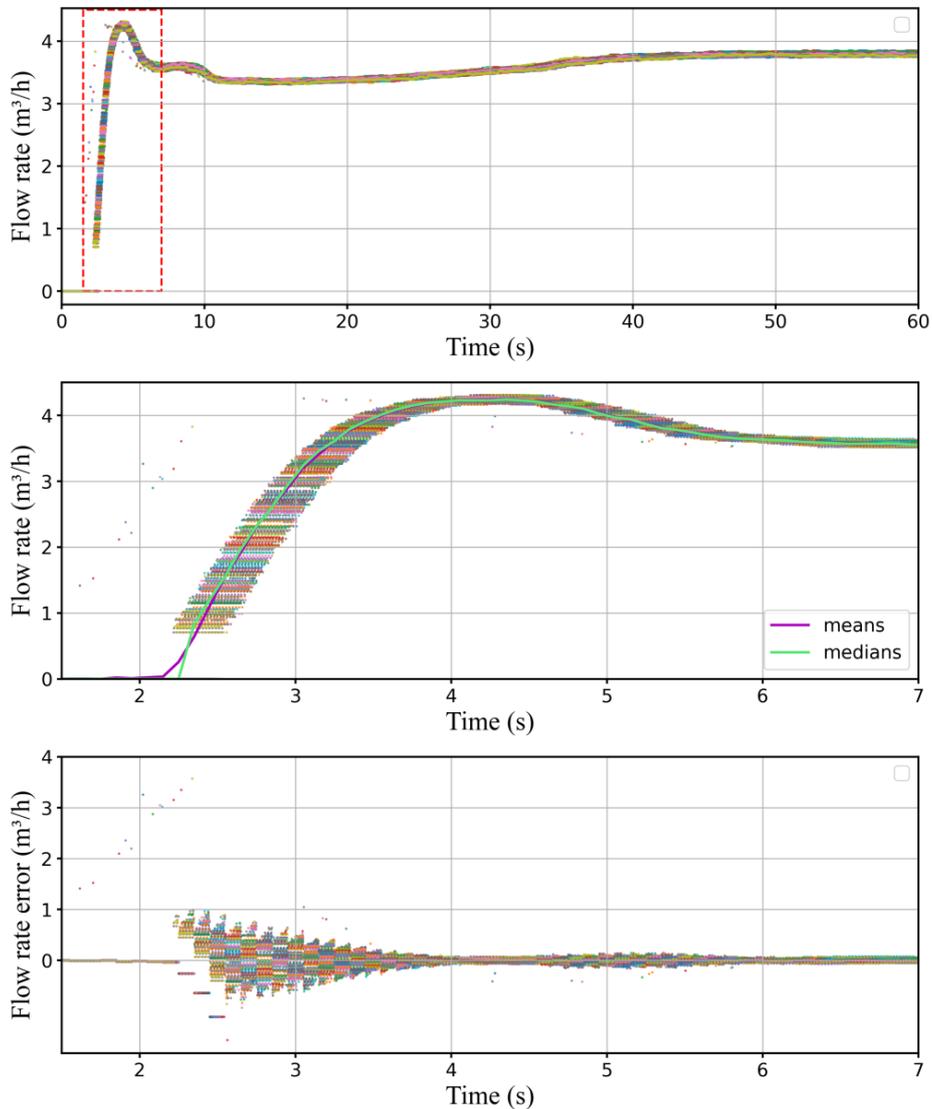


Fig. 2. Flow rates and flow rate errors vs. time in response to 89 repetitive inverter frequency changes (colour points) and the plot of averages (magenta) and medians (green) calculated for each time sample.

between input quantities and the resulting waveform. While this is an intriguing direction, it is also a complex one. Artificial intelligence techniques could assist in this analysis, but they require extensive datasets for effective training. Signal pre-processing methods such as filtering and thresholding may also be applied. However, while these techniques are effective in offline analysis, they can negatively impact system dynamics during real-time processing.

Accepting visible signal scatter introduces measurement errors. Whether this is tolerable depends on the specific application. In the collected plots, some exhibit diverse

dynamic responses that result in significant errors. In the context of DTs, where the VM must adapt dynamically to the PA, such unrepeatability—especially in the absence of observable drift—can lead to unnecessary model tuning. This tuning may not yield any improvement in overall system performance.

No algorithm can correct random errors. Therefore, building a reliable virtual model based on data affected by such errors is not feasible. Moreover, it is often unclear whether the observed variability stems from measurement errors or is an inherent property of the system.

From a reliability perspective, the system shown in

Fig. 1 functions as a series connection of all its elements. These elements include both components shown on this figure and connections between them. This means it operates correctly only when every element remains operational. Its overall availability equals the product of the availabilities of each individual element. Industry demands extremely high availability, along with other reliability indicators. Consequently, for DTs to be usable in industrial settings, all components must demonstrate a high level of technological maturity. Until this maturity is achieved, widespread industrial utility will remain constrained. For simpler tasks, however, the current level of maturity is sufficient, and DTs are already being applied successfully.

IV. CONCLUSION

In this work, we began by defining the concept of a DT and illustrating it with a conceptual diagram. We then reviewed the most significant current and potential applications, noting that many remain largely hypothetical. Following this, we outlined the key requirements for constructing a reliable virtual model.

We provided background on the application of DTs in water pipeline systems and presented experimental data from our own laboratory setup. These results revealed non-repeatable system behaviour, prompting a discussion on the implications for developing virtual models based on such uncertain dynamics. We concluded that, in certain cases, further refinement of the model may not be economically justified.

Finally, we examined the limited real-world adaptation of DTs through the lens of system reliability. We argued that successful implementation depends on the technological maturity and reliability of all system components. Until these conditions are met, the widespread deployment of DTs will remain constrained. However, for simpler tasks where component maturity is sufficient, DTs are already proving to be effective.

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