Digital Twin and Foundation Models: A New Frontier

Athanasios Trantas[a] and Paolo Pileggi[b]
Advanced Computing Engineering, Unit ICT, Strategy & Policy, TNO, The Netherlands

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Abstract: A Foundation Model (FM) possesses extensive learning capabilities; it learns from diverse datasets. This is our opportunity to enhance the functionality of Digital Twin (DT) solutions in various sectors. The integration of FMs into the DT application is particularly relevant due to the increased prevalence of Artificial Intelligence (AI) in real-world applications. In this position paper, we begin to explain a novel perspective on this integration by exploring the potential of enhanced predictive analytics, adaptive learning, and improved handling of complex data within DTs — by way of designated purposes. Ultimately, we aim to uncover hidden value of enhanced reliable decision-making, whereby systems can make more informed, accurate and timely decisions, based on comprehensive data analytics and predictive insights. Mentioning selected ongoing cases, we highlight some benefits and challenges, like computational demand, data privacy concerns, and the need for transparency in AI decision-making. Underscoring the transformative implications of integrating FMs into the DT paradigm, a shift towards more intelligent, versatile and dynamic systems becomes clearer. We caution against the challenges of computational resources, safety considerations and interpretability. This step is pivotal towards unlocking unprecedented potential for advanced data-driven solutions in various industries.

1 INTRODUCTION

The concept of Digital Twin (DT) and the Foundation Model (FM) represents a confluence of real-world and digital realms, each with its transformative potential. Digital twins, as defined by the Digital Twin Consortium, are virtual representations of real-world entities and processes, synchronised at specific frequencies and fidelity (Digital Twin Consortium, 2023). The DT paradigm uses real-time and historical data to mirror and understand real-world systems and their processes throughout their entire life-cycle. Utilising sensors or other data-producing mechanisms, the digital twin and its real-world counterpart can achieve synchronisation with a high degree of detail, as depicted in Figure 1. The digital twin processes experimental inputs (such as configuration parameters) and yields model outputs. Conversely, the real twin gathers feedback from the real world and can enact changes in its environment. Synchronisation of the digital twin occurs via state updates received from the real twin, while the digital twin can guide the real twin through state predictions or control commands (Semeraro et al., 2021). Digital twins are increasingly prevalent across various sectors, including manufacturing, healthcare, urban planning and environmental monitoring (Barricelli et al., 2019). They serve as synchronised models for real-world systems or objects, while the DT Applications (DTA) that employ them serve one or more purposes, like improved decision-making, predictive maintenance and system optimisation. This requires the digital twin to interact with the digital environment and possibly other digital twins, as the figure suggests.

FMs represent a paradigm shift in AI. Exemplified by large-scale Machine Learning models, like *Generative Pre-trained Transformer 3* (Brown et al., 2020), *Bidirectional Encoder Representations from Transformers* (Devlin et al., 2018) and *Contrastive Language Image Pre-training* (Radford et al., 2021)) that are trained on extensive and diverse datasets. A key characteristic is their ability to adapt to a wide range of tasks and domains, leveraging their capacity to generalise from the training data (Yuan, 2023) — generally using self-supervision (Hinton et al., 2006) at scale. They have shown remarkable capabilities in understanding and generating human language, photorealistic images and videos; with potential in various applications — from automated content creation to complex decision-making (Yang et al., 2023).

[a] https://orcid.org/0000-0001-7109-9210
[b] https://orcid.org/0009-0001-6031-201X

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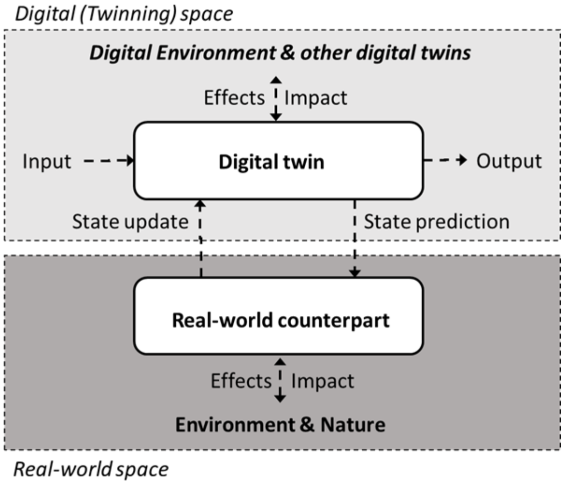

Figure 1: Interaction between the digital twin and its real-world counterpart.

Following (Bommasani et al., 2021), our work uses the term *Foundation Model* to describe a broad paradigm shift in AI that encompass models like pre-trained models, self-supervised models, large language models, language vision models, general purpose models, multi-purpose models, and task-agnostic model. This term encompasses their fundamental role: While these models are initially incomplete, they provide a base for developing numerous task-specific models through adaptation. It highlights the importance of stability, safety and security in their architecture. The concept of FMs is shown in Figure 2. Particularly, in this figure, we position the FM system concept in the DT paradigm in line with how DT is presented in Figure 1.

The integration of FMs in the DT paradigm is promising: It suggests a synergy where the adaptive and extensive learning capabilities of FMs can enhance the predictive accuracy, operational efficiency and decision-making processes in the DTA, as suggested by Figure 1. This integration could lead to twins that are not only representative of their real-world counterparts but also capable of anticipating future states, adapting to changes with minimal human intervention and devising plans. In addition, this synergy can pinpoint a new way to interact and configure systems in real-time.

To the best of the authors' knowledge, there appears to be no literature on the explicit or direct integration of FMs with digital twins. While there are examples of AI being used in DTA for applications like predictive maintenance and system optimisation (Pileggi et al., 2021), the specific application of FMs in such a context is scarce. This intersection offers a rich area for exploration, posing new opportunity with significant challenge.

In Sec. 2, we mention related work. We then proceed to delve into the potential integration of FMs with digital twins by highlighting areas of applicability with so-called designated purposes in Sec. 3. In Sec. 4, we explore benefits, challenges and practical considerations. Finally, in Sec. 5 we conclude with a discussion and mention future work.

2 RELATED WORK

The integration of AI in the DT pradigm has been a subject of increasing interest in both academic and industrial research. While the specific incorporation of FMs in DT is relatively uncharted, there is a growing body of work highlighting the use of AI formal methods in enhancing the capabilities of DTs (Rathore et al., 2021). Below, we present a comprehensive and cohesive narrative on the role of AI in echancing DTs across various domains.

Aerospace: In the aerospace industry, the synergistic integration of AI with DTAs represents a significant technological advancement in system design, maintenance and operational efficiency. The role of AI in this domain is multifaceted, encompassing advanced simulations, predictive analytics and enhanced fault diagnostic capabilities within DT frameworks. This integration facilitates a high-fidelity representation of aerospace systems, empowering real-time monitoring and predictive assessments of structural and functional parameters (Allen, 2021). The incorporation of AI algorithms into DTs enables the extraction of insightful data from complex aerospace dynamics, aiding in the optimisation of design processes, the elevation of safety standards, and the refinement of strategic decision-making protocols (Hänel et al., 2020).

Environmental Sciences: AI-enhanced DTs are also being employed to assist the analysis of complex systems, environmental monitoring and management (Pylianidis et al., 2022). For instance, models that simulate and predict environmental changes, such as those impacting biodiversity, are increasingly incorporating AI for more accurate and timely predictions (Trantas et al., 2023). Projects like Destination Earth (Nativi et al., 2021) that seek to build a digital twin of the Earth use advanced data management systems and data-driven AI technologies to generate deep insights from complex real-world processes and interpret them to produce actionable intelligence.

Healthcare: In the this sector, AI-driven DTAs are being explored for personalised patient care and treatment. A notable example is the use of DTs in patient-specific models for predicting disease pro-

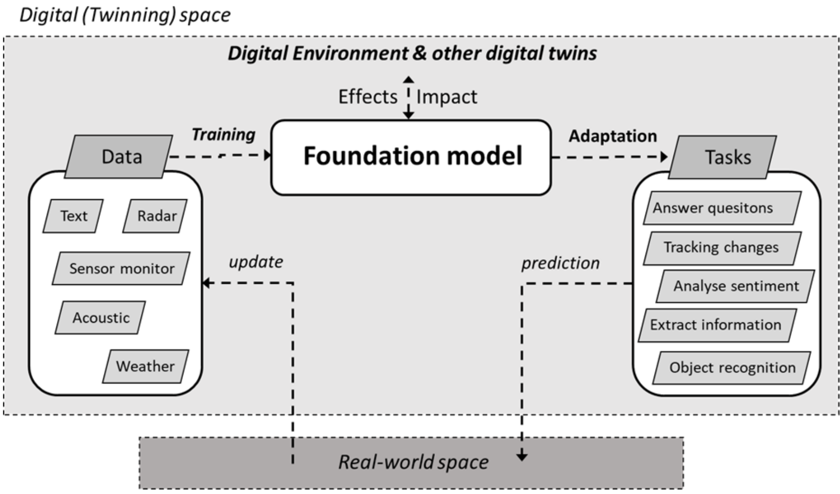

Figure 2: An FM system, adapted from (Bommasani et al., 2021), envisioned as a digital twin with the capacity to consolidate different data modalities from multiple sources, where the model output can be adapted to an array of specific downstream tasks.

gression and treatment outcomes. These models utilise AI algorithms to analyse patient data and provide personalised treatment recommendations (Kaul et al., 2023).

Manufacturing: In manufacturing, digital twins have become instrumental in advancing smart and flexible manufacturing, fault diagnosis, robotic assembly, quality monitoring and job shop scheduling. AI algorithms are increasingly being integrated into DTAs for manufacturing and supply chain optimisation. This involves using AI for analysing production data and optimising supply chain logistics and production plans, seamlessly integrating multiple topological plant instances and predicting market demands (Mo et al., 2023; Vyskočil et al., 2023).

Predictive Maintenance: A widely recognised application of AI in DT is in predictive maintenance. For instance, a study detailed in the so-called *Digital Twin Primer* outlines the use of AI for predictive maintenance in manufacturing (Borth and Broekhuijsen, 2020). By including AI algorithms in DTAs, manufacturers can anticipate equipment failures and schedule maintenance, thereby reducing downtime and extending equipment life (van Dinter et al., 2022).

Smart Cities and Urban Planning: In urban planning, AI-driven DTAs are used for optimising city operations and infrastructure management. These applications employ AI algorithms to analyse data from various urban systems, enabling city planners to simulate and test different scenarios for urban development and smart mobility. An solution proposed by (Seuwou et al., 2020), connected autonomous vehicles are build on top of intelligent transportation systems and can influence the growth of digital economies in large cities and alleviate problems like excessive traffic jams, road accidents, CO_2-emissions and public health deterioration.

Despite these advancements, the specific application of FMs, which are more generalist and capable of learning from diverse data sets, in DT is still emerging. Current research predominantly focuses on more traditional AI algorithms tailored to specific tasks within DT. The potential of FMs to enhance the adaptability, predictive and autonomy power of DT represents an exciting, albeit relatively unexplored, research avenue.

While the role of AI in advancing DTAs is well-established across various sectors, the integration of FMs into this domain remains an area ripe for exploration. This research gap presents an opportunity to develop more advanced, versatile and efficient DT solutions by leveraging the broad applicability and learning capabilities of FMs.

3 DESIGNATED PURPOSES

The integration of FMs into the DT paradigm offers a new dimension of functionality and potential. These models can contribute significantly to the evolution of DTs, especially in areas requiring complex data interpretation, predictive analytics, adaptive learning and autonomous decision making. Main contribution areas highlighted by the synergy of FM and digital twins, which we refer to as designated purposes, are as follows.

Enhanced Predictive Analytics: FMs, with their ability to process and learn from vast datasets, can significantly enhance the predictive capabilities of DTs.

For instance, in the manufacturing sector, FMs can analyze patterns from historical and real-time data to predict equipment failures or maintenance needs more accurately than traditional models. This capability aligns with the findings in the *Digital Twin Primer* mentioned before, emphasising the importance of predictive maintenance in manufacturing using DTAs.

Adaptive Learning and Evolution: Unlike traditional models that require retraining or adjustments for new scenarios, FMs can continuously evolve by learning from new data inputs. This characteristic is particularly beneficial for digital twins representing complex and dynamic systems, such as urban infrastructures (Takeda et al., 2023) or environmental models, where conditions can change rapidly and to significant extremes. The adaptive nature of FMs can help digital twins remain accurate and relevant over time, reflecting real-world changes more effectively.

Complex Data Interpretation and Simulation: FMs are adept at handling and interpreting complex, unstructured data, which is a common challenge in DT. In healthcare, for example, DTAs can leverage FMs to interpret diverse patient data, leading to more personalised and accurate healthcare solutions. This use case resonates with the healthcare applications mentioned in the literature, where AI-driven patient-specific models are becoming increasingly prevalent. For environmental sciences, a recent example is the Harmonised Landsat and Sentinel-2 Geospatial FM that can support applications that include tracking changes in land use, monitoring natural disasters and predicting crop yield (NASA and IBM, 2023).

Generalisation Across Domains: A significant contribution of FMs is their ability to generalise across different domains and tasks. This feature can be incredibly advantageous for digital twins used in multidisciplinary fields or applications requiring cross-domain knowledge. For instance, in robotics an FM trained on datasets of diverse robot demonstrations can offer a generalist model that controls many different types of robots, following diverse instruction, perform basic reasoning about complex tasks and generalise effectively (Open X-Embodiment Collaboration, 2023). In healthcare, (Moor et al., 2023) proposed Generalist Medical AI – an FM concept that can offer bedside decision support, grounded radiology reports and augmented procedures across numerous medical tasks.

System Verification: In contrast with traditional AI models designed for specific tasks, FMs can handle a wide range of tasks, making it difficult to anticipate all potential failures. Therefore, developers and regulators must ensure thorough testing and clarify approved uses. Interfaces should alert users about ”off-label usage” to prevent misinformation. Verification of these models requires multidisciplinary panels, as they process complex inputs and outputs, demanding collaborative efforts for accurate assessment.

Computational Demand and Resource Intensity: The implementation of FMs as DT components demands significant computational resources, which can be a limiting factor, especially for smaller-scale applications.

Data Privacy and Security: The vast amount of data required to train FMs raises concerns about data privacy, particularly in sensitive domains like healthcare.

Model Interpretability: FMs, particularly because of their architecture and size, often lack transparency in their decision-making processes, which can be a critical issue in scenarios where reasoning and explainability is essential.

4 CASE ANALYSES

The potential integration of FMs into the DT paradigm can be best understood through specific case analyses. Here, we examine three scenarios to explore the potential benefits and challenges of this integration. In these examples, FMs are positioned at the core representation models of the DTA.

Case 1: Manufacturing Process Optimisation

A. Potential Benefits of Integration:

- *Enhanced Predictive Maintenance:* Leveraging FMs in manufacturing DTAs can significantly improve predictive maintenance. These models can analyse complex patterns from machine operation data, identifying potential issues before they lead to downtime.
- *Optimised Production Processes:* FMs can be used to represent various production scenarios simultaneously, using real-time and historical data, leading to more efficient and cost-effective manufacturing processes.

B. Integration Challenges:

- *Real-Time Data Processing:* Manufacturing DTAs require rapid processing and analysis of data. FMs, due to their size and complexity, could struggle with real-time data analysis, leading to delays in crucial decision-making.
- *Model Pre-training and Fine-tuning:* Manufacturing environments are highly specific, varied and produce a lot of data from sensors. Customising FMs and adapting them to accurately

reflect the nuances of each manufacturing process could be resource-intensive and technically challenging.

Case 2: Biodiversity Conservation Planning

A. Potential Benefits of Integration:

- *Enhanced Data Harmonisation and Analysis:* Using FMs in biodiversity DTAs can increase the efficiency on data fragmentation by consolidating and analysing dispersed and multimodal data sources. This ability can lead to more comprehensive and insightful ecological analyses, enhancing the effectiveness of biodiversity research.
- *Sophisticated Modelling of Complex Ecological Systems:* Leveraging FMs can significantly improve the modelling of complex ecological systems. Their advanced machine learning algorithms and adaptability allow for a deeper understanding of complex, less understood ecological dynamics. By assimilating these models with DTs, researchers can develop more nuanced and accurate representations of ecological systems, addressing the challenges of complexity and scalable inter-model coordination. FMs can assist by aligning species-specific models within a broader ecological context, matching various temporal resolutions and levels of abstraction with real-world ecological processes.
- *New ways for User Interfacing:* DTAs are mainly centered around the monitoring, prediction and control elements of the underlying processes than are being modelled, often lacking effective and interactive user experience. FMs can complement this part by offering instruction-based interfacing through text, voice and visual queues while in the same time allowing for easier model configuration with limited expert knowledge.

B. Integration Challenges:

- *Real-time Data Processing, Monitoring and Fine-tuning:* Traditional methods, such as static species distribution maps, lack real-time updating capabilities. Integrating FMs with DTAs requires the development of systems capable of real-time data processing and monitoring to provide up-to-date ecological information. This challenge involves not only the technical aspect of real-time data handling but also ensuring the continuous flow and integration of dynamic ecological data into the models. Additionally, efficient algorithms for fine-tuning the FMs on the dynamic datasets are required.
- *Complexity in Addressing Uncertainties:* The inherent limitations in current methods to identify uncertainties and knowledge gaps in ecosystems make integration complex. FMs need to be sophisticated enough to address these uncertainties effectively, which can be a significant technical and methodological challenge.
- *Achieving Scalable Inter-Model Coordination:* The integration of species-specific models within a generic ecological model is challenging due to varying research objectives and time scales. FMs in DTAs must be designed to match the diverse temporal resolutions and abstraction levels of different models with real-world ecological processes. This requires a delicate balance between the granularity of the data, the scope of the models, and the overarching ecological dynamics they aim to represent.

Case 3: Smart City Infrastructure Management

A. Potential Benefits of Integration:

- *Comprehensive Urban Simulation:* FMs can assimilate data from various urban systems (traffic, utilities, public services) to represent and predict urban dynamics, aiding in more effective city planning and management.
- *Adaptive Response to Urban Challenges:* These models can help DTs adapt to changing urban environments, such as fluctuating traffic patterns or utility usage, ensuring efficient and sustainable city operations.

B. Integration Challenges:

- *Complex Data Integration:* Integrating and processing data from diverse urban systems pose significant challenges, requiring advanced data harmonisation and management strategies.
- *Ethical and Privacy Concerns:* The use of extensive urban data in FMs raises concerns about individual privacy and data ethics, necessitating stringent data governance protocols.

By no means is our analysis of each case exhaustive. They serve as an initial insight into the potential value and wide range of challenges that arise. However, in all cases, the integration of FMs in the DTA seems to offer substantial benefit, particularly in terms of improved and enhanced representation, prediction, planning and generalisation capabilities. Moreover, DTAs can greatly benefit from the FMs ability to handle complex, multi-modal data. FMs can offer new ways for end-users to engage with DTAs.

5 CONCLUSION AND FUTURE WORK

In this paper, we make an initial attempt at explaining a novel perspective that makes explicit the direct integration of FMs in DT. This exploration opens up a new frontier in the intersection of AI and real-world applications. In this paper we delve into the potential of this integration, highlighting its transformative implications across various sectors – from manufacturing and healthcare, to biodiversity and aerospace. The key value highlights explored further in our case analyses are as summarised as follows.

- **Enhanced Capabilities:** The integration of FMs with digital twins promises enhanced predictive analytics, adaptive learning capabilities, and superior handling of complex multi-modal data. This integration can lead to more accurate, efficient, and dynamic DT solutions.
- **Broad Applicability:** Known for their versatility, FMs can be adapted to diverse DTAs, from optimising manufacturing processes to personalising healthcare treatments.
- **Continuous Evolution:** Unlike conventional models, FMs can help enable digital twins to evolve continuously, learning from new data and adapting to changes in their real-world counterparts.

Future work should address the following challenges.

- **Computational and Resource Demands:** The implementation of FMs in DTAs is computationally intensive, necessitating significant processing power and specialised expertise.
- **Data Privacy and Safety Concerns:** In sectors like healthcare, the use of extensive and sensitive data in FMs raises critical questions about privacy, security, and ethical usage.
- **Transparency and Interpretability:** The often opaque nature of the FM decision-making processes poses challenges in scenarios where explainability is crucial.

The potential integration of FMs into DTAs is an exciting development that stands to revolutionise various sectors by providing more intelligent, adaptable and efficient systems. However, realising this potential will require addressing significant challenges, including managing computational demands, ensuring data privacy and enhancing model transparency.

As we move forward, it is crucial to continue exploring this integration with a focus on safe, responsible and ethical AI practices. The journey towards fully realising the potential of FMs in DT will involve interdisciplinary collaboration, continuous research and a commitment to overcoming the technical and ethical challenges that lie ahead.

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