ESSENCE OF DIGITAL TWINS

Laura Mainini
Politecnico di Torino, Torino, Italy
e-mail: laura.mainini@polito.it

Matteo Diez
CNR-INM, Consiglio Nazionale delle Ricerche–Istituto di Ingegneria del Mare, Rome, Italy
e-mail: matteo.diez@cnr.it

This extended abstract discusses the mathematical aspects that underpin the concept (and the essence) of digital twins as purpose-driven adaptive models (or virtual representations) and that are essential to their formalization for applications to science and engineering including product design, development, maintenance, and operations.

Keywords: *digital twins, systems design and development, systems maintenance, operations*

1. Introduction

Digital twins are widely considered as enablers of groundbreaking changes in the development, operation, and maintenance of novel generation of products. In this context, "a Digital Twin is a set of virtual information constructs that mimics the structure, context, and behaviour of an individual/unique physical asset, is dynamically updated with data from its physical twin throughout its lifecycle, and informs decisions that realize value" [1].

While there is a popular—frequently misleading—understanding of digital twins as the highest-fidelity virtual representation of all aspects of the real system of interest, digital twins are rather purpose-driven virtual representations. Therefore, those digital counterparts of an individual real artifact are not unique but would assume different forms depending on the purpose [2]. At the same time, all digital twins share a key property that distinguish them from the parent family of digital models: digital twins are physics-based and adaptive in nature, and are conceived to continuously learn from data. As such, digital twins are inevitably characterized by a mathematical soul to combine data streams and physics-based representations in a principled and efficient way.

Methods are rooted at the intersection of scientific computing and machine learning, and span the world of multi-fidelity and multi-source information fusion or calibration, data assimilation, surrogate and reduced order modelling, uncertainty quantification, optimal data selection and acquisition. Major research open challenges relate to the rapidity and the reliability of responses and predictions from the digital representations.

This extended abstract discusses the mathematical aspects that underpin the concept (and essence) of digital twins as purpose-driven adaptive models (or virtual representations) and that are essential to their formalization for applications to science and engineering including product design, development, maintenance, and operations. Based on the definitions of digital twin proposed by international communities over the years, this work aims at providing an overview of the mathematical formulations and computational methods associated to digital twinning. Considerations will also be drawn upon the perspectives of a multidisciplinary and cross-domain forum to identify the main challenges met to enable responsive, predictive and reliable digital twins, and the associated research avenues.

2. Purpose-driven adaptive models

A digital twin is a virtual model of a system or process that progressively adapts and specializes by learning from data from the real counterpart. The value introduced by the availability and adoption of digital twins relates to their usefulness—all models are wrong, some are useful [3]—in providing reliable and timely predictions to inform decisions along the entire product life cycle. The time- and resource-efficiency requirements impose digital twins of a given physical system or process not to be unique, but rather multifaceted and purpose-driven adaptive models, because there is not such a *twin that rules them all*. The principle of model usefulness discards the definition of digital twin as a “high-fidelity model of the system which can be used to emulate the actual system” [4] in favour of a synthesis of “the best available models, sensor information, and input data to mirror and predict activities/performance over the life of its corresponding physical twin” [5].

These features require digital twins to be endowed with fine mathematical souls tasked to formulate, compute and update the virtual models as dynamic syntheses of physics formalizations and data streams to inform decisions with reliable predictions. In particular, data assimilation methods are pivotal to the realization of models that continuously morph by learning from data. Whether the assimilation is achieved via calibration or fusion approaches, computational methods for multisource information synthesis are essential to realize digital twins whose data sources can be diverse – sensor measurements, signal acquisitions, experimental databases, (*50-shades-of-grey*) models evaluations, physics based simulations. Among those, multifidelity methods also acknowledge that multiple representations of given physical systems and processes are possible at different levels of accuracy and costs, which offer tremendous opportunities to play across multiple levels of abstractions to maximize the usefulness with respect to the specific decision tasks to support [6].

The same usefulness rationale motivates the role of (non-intrusive) surrogate modelling for digital twins, and the specific need of formulations that allow to learn models from a limited amount of observations (small data) and somehow characterize the reliability of the estimated predictions. This requirement poses major limitations to the straight-forward use of fashionable deep learning and purely data-driven methods—which are data intensive and of questionable reliability—and demands for advanced approaches that could ideally embed physical constraints in the learning process. Examples include formulations for data-driven operator inference [7], projection based model reduction for physics-based machine learning [8], physics informed neural networks [9], and domain aware active learning [10].

In addition, the development and adoption of digital twins for platforms and systems is often affected by the challenges associated with the high-regret scenarios faced over the operational life, where badly informed decisions can lead to catastrophic consequences. This demands mathematical methods to characterize the reliability of the predictions provided by the digital twins in support of the decisional processes. On the one hand, computational methods for uncertainty quantification, characterization and propagation [11] are essential to approach these open questions and equip the predictions with forms of reliability measures or robustness bounds [12]. On the other hand, research efforts demonstrated the importance of the quality of source data over their quantity [13] to improve reliability and robustness of the predictions, which motivates the recommendation to pay larger attention to the field of optimal sensor placement, and optimal data selection and acquisition for purpose-driven digital twins [14].

As the digital twins ideally evolve (or degrade) together with the real/physical system along its life cycle, any mandate to represent the as-built system is intrinsically relaxed. Moreover, whether or not a digital twin could exist prior to (without) the corresponding physical twin is still open debate. Indeed, the twins are ideally continuously informed and enabled through the digital thread that links all the stages of a system life [15] with forward and backward feeds: limiting their existence to specific phases would introduce ontological and taxonomic inconsistencies.

3. System design, development, maintenance, and operations

This section briefly outlines how the digital twins have been/can be used to support decisions at design, manufacturing, operational, maintenance stages, even when the physical system does not yet exist.

Digital twins for systems design and development. Digital twins are used in system design and development to simulate, test, and refine/optimize new products or processes [16]. Digital twins are used to explore design spaces and advance the development of products. In this phase the digital twin lacks its physical counterpart, nevertheless it shall include all the relevant feature of its physical twin once the latter will be brought to life. The purpose of the digital twin could be to predict the product performance once in operation (design for performance) or to assess its manufacturability and prediction costs (design for manufacturability). Depending on the application, these can be achieved by a product digital shadow (focusing on the mathematical modeling of the relevant physical attributes) or digital replica (an automatic projection of the system construction), respectively [17].

Digital twins for systems maintenance. Maintenance practices benefit from digital twinning by using virtual representations of physical assets and systems, which integrate real-time data from sensors into the relevant mathematical models. By providing real-time, data-driven models of asset state and performance, digital twins enable predictive [18] and prescriptive maintenance [19], preventing downtime and reducing maintenance costs. Digital twins may be used to optimize maintenance schedules, troubleshoot issues, and develop more efficient maintenance procedures. Digital twins can be used to explore different maintenance scenarios with the aim of finding the most effective solutions before application in the physical world.

Digital twins for operations. In the context of optimizing operations, digital twins can play an essential role by providing insights into how assets and systems are operating in real-time, allowing for proactive decision making [20]. The latter can be extended to model-predictive control by incorporating system state forecasts provided by digital twins [21]. Moreover, digital twins enable virtual testing in different operating scenarios, reducing the need for physical testing, the risk of damaging the physical asset, and the testing overall cost. Environment digital twins are a research frontier for a fully integrated digital twin including the asset and the environment of operations [22].

REFERENCES

1. Committee, A. D. E. I., et al. Digital twin: Definition & value, *AIAA and AIA Position Paper*, (2020).

2. Rasheed, A., San, O. and Kvamsdal, T. Digital twin: Values, challenges and enablers from a modeling perspective, *Ieee Access*, **8**, 21980–22012, (2020).

3. Box, G. All models are wrong, but some are useful, *Robustness in Statistics*, **202** (1979), 549, (1979).

4. Board, S. E., (2022), *The Guide to the Systems Engineering Body of Knowledge (SEBoK), v. 2.7*.

5. West, T. D. and Blackburn, M. Is digital thread/digital twin affordable? a systemic assessment of the cost of dod's latest manhattan project, *Procedia computer science*, **114**, 47–56, (2017).

6. Beran, P. S., Bryson, D., Thelen, A. S., Diez, M. and Serani, A. Comparison of multi-fidelity approaches for military vehicle design, *AIAA AVIATION 2020 FORUM*, p. 3158, (2020).

7. Peherstorfer, B. and Willcox, K. Data-driven operator inference for nonintrusive projection-based model reduction, *Computer Methods in Applied Mechanics and Engineering*, **306**, 196–215, (2016).

8. Swischuk, R., Mainini, L., Peherstorfer, B. and Willcox, K. Projection-based model reduction: Formulations for physics-based machine learning, *Computers & Fluids*, **179**, 704–717, (2019).

9. Raissi, M., Perdikaris, P. and Karniadakis, G. E. Physics-informed neural networks: A deep learning framework for solving forward and inverse problems involving nonlinear partial differential equations, *Journal of Computational physics*, **378**, 686–707, (2019).

10. Di Fiore, F., Maggiore, P. and Mainini, L. Multifidelity domain-aware learning for the design of re-entry vehicles, *Structural and Multidisciplinary Optimization*, **64**, 3017–3035, (2021).

11. Le Maître, O. and Knio, O. M., *Spectral methods for uncertainty quantification: with applications to computational fluid dynamics*, Springer Science & Business Media (2010).

12. Yao, W., Chen, X., Luo, W., Van Tooren, M. and Guo, J. Review of uncertainty-based multidisciplinary design optimization methods for aerospace vehicles, *Progress in Aerospace Sciences*, **47** (6), 450–479, (2011).

13. Mainini, L. and Willcox, K. E. Data to decisions: Real-time structural assessment from sparse measurements affected by uncertainty, *Computers & Structures*, **182**, 296–312, (2017).

14. Mainini, L. and Willcox, K. E. Sensor placement strategy to inform decisions, *18th AIAA/ISSMO Multidisciplinary Analysis and Optimization Conference*, p. 3820, (2017).

15. West, T. D., (2019), *Hopes, Dreams, and Challenges of Digital Nirvana: The State of the Art and the Art of the Possible in Digital Twin and Digital Thread*. American Institute of Aeronautics and Astronautics, Inc.

16. Jones, D., Snider, C., Nassehi, A., Yon, J. and Hicks, B. Characterising the digital twin: A systematic literature review, *CIRP Journal of Manufacturing Science and Technology*, **29**, 36–52, (2020).

17. Fuller, A., Fan, Z., Day, C. and Barlow, C. Digital twin: Enabling technologies, challenges and open research, *IEEE Access*, **8**, 108952–108971, (2020).

18. van Dinter, R., Tekinerdogan, B. and Catal, C. Predictive maintenance using digital twins: A systematic literature review, *Information and Software Technology*, p. 107008, (2022).

19. Errandonea, I., Beltrán, S. and Arrizabalaga, S. Digital twin for maintenance: A literature review, *Computers in Industry*, **123**, 103316, (2020).

20. Gonzalez, M., Salgado, O., Croes, J., Pluymers, B. and Desmet, W. A digital twin for operational evaluation of vertical transportation systems, *Ieee Access*, **8**, 114389–114400, (2020).

21. McClellan, A., Lorenzetti, J., Pavone, M. and Farhat, C. A physics-based digital twin for model predictive control of autonomous unmanned aerial vehicle landing, *Philosophical Transactions of the Royal Society A*, **380** (2229), 20210204, (2022).

22. Lee, J.-H., Nam, Y.-S., Kim, Y., Liu, Y., Lee, J. and Yang, H. Real-time digital twin for ship operation in waves, *Ocean Engineering*, **266**, 112867, (2022).