On key technologies for realising digital twins for structural dynamics applications

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Abstract

The term digital twin has gained increasing popularity over the last few years. The concept, loosely based on a virtual model framework that can replicate a particular system for contexts of interest over time, will require the development and integration of several key technologies in order to be fully realised. This paper, focusing on vibration-related problems in mechanical systems, discusses these key technologies as the *building blocks* of a digital twin. The example of a simulation digital twin that can be used for asset management is then considered. After briefly discussing the building blocks required, the process of data-augmented modelling is selected for detailed investigation. This concept is one of the defining characteristic of the digital twin idea, and using a simple numerical example, it is shown how augmenting a model with data can be used to compensate for the inherent model discrepancy. Finally the implications of this type of data augmentation for future digital twin technology is discussed.

Key words: digital twin, dynamics, mechanical, virtualisation, vibration

1 Introduction

The digital twin concept is based on creating a virtual model framework that can replicate a particular system for contexts of interest over time. For example, a digital twin can be considered as a process, a product or some combination of both. At the most basic level, a digital twin is defined as a virtual duplicate of an engineering system built from a combination of models and data. In this sense the digital twin is more than just a computer-based simulation of the system of interest. Most importantly, the digital twin should have the ability to be used as a predictive tool to inform key engineering decisions, and it will be argued that this is one of its defining characteristics. A good introduction to the idea of the digital twin, including the background and history of the topic, is given by Datta [1–3].

There are multiple other examples of using the digital twin concept for engineering applications in the literature. For example, improving manufacturing processes [4–6], additive manufacturing [7,8], aerospace engineering [2,9], offshore drilling [3], product design [10–13] and nuclear fusion [14]. All these applications can be categorised into broad classes of tasks that the digital twin is being asked to achieve (with considerable overlap). In the context considered here, this will specifically be to make predictions for condition or structural health monitoring (SHM) purposes, and to understand the current state of the physical twin.

The aim of this paper is to show an example of how a digital twin can be built for engineering applications which have time-dependent (dynamic) behaviour. The key building blocks required to create a simulation digital twin will be discussed. A key characteristic of a digital twin is the ability to bring together models and data, in order to give more accurate predictions. To demonstrate one approach to achieving this, the process of data-augmented modelling is considered in detail. To illustrate the concepts described an engineering based example is presented. A companion paper to this one presents a mathematical framework for the digital twin paradigm [15].

2 Building a digital twin

The primary aim of creating a digital twin is to enable the user to have as much information as possible about the current status and future behaviour of the physical twin. To set the context for this, a schematic hierarchy of possible capabilities for a digital twin is shown in Figure 1. Here it can be seen that there are currently five levels of sophistication for

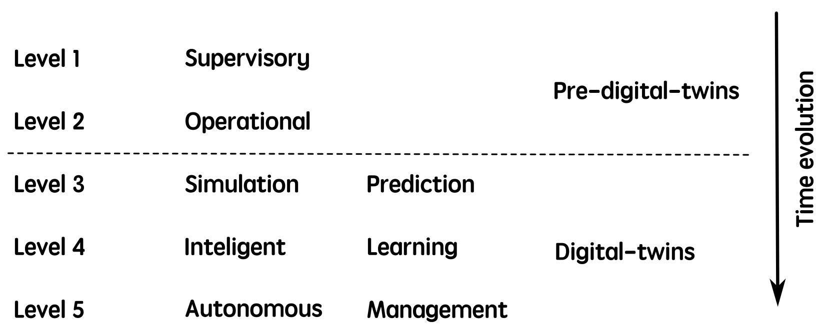


Figure 1: A capabilities hierarchy for digital twins, where each level incorporates all the previous capabilities of the levels below.

a digital twin, starting at the lowest level of sophistication with Level 1, and increasing to Level 5, with each level incorporating the functionality of all previous levels. In fact three key requirements of a digital twin, namely *supervision*, *learning* and *management* are captured by Levels 3 to 5 respectively. To capture the historical time evolution, Levels 1 and 2 are included, but not considered further.

An key distinguishing feature of a digital twin (and hence the dividing line between Levels 2 and 3 in Figure 1) is that it can be used as a predictive tool. Furthermore, despite the focus on asset management tasks, all types of digital twin should evolve over the life-time of the physical twin. As a result they can be used in different contexts, depending on the life stage of the physical twin, whilst remaining a close one-to-one mapping from physical to digital. For example, if required, a digital twin can be used in the design phase of the physical twin, as described in Tugel *et al.* [2]. Following that, the digital twin can be used in the manufacture and commissioning stage. Then, the digital twin can be used for asset management through operation and maintenance of the physical twin right through to end of life and decommissioning. Finally it is noted that the optimum final embodiment of the digital twin is in the form of a piece of software with highly informative graphical outputs.

2.1 Objectives of a digital twin

The precise objectives of the digital twin will depend on the context that is required, but a typical simulation-twin should allow the user to:

- understand the outputs quickly, in real-time if required, with visualisation of results;
- incorporate and update the geometry of the digital twin through integrated computer-aided-design (CAD) and data processes with a clear measure of fidelity;
- tunnel through the full-system CAD to specific components or sub-assemblies of interest and perform isolated tasks;
- navigate a hierarchical representation of physical behaviour at different length scales;
- interrogate the current state of the structure, whether in real-time or historically and perform data analysis (diagnosis);
- test multiple scenarios to predict likely future outcomes (prognosis & decision support);
- design controllers, perform hardware-in-the-loop simulation and/or set control processes for the physical twin;
- quantify a level of confidence (trust) that the user should ascribe to given outputs;
- generate test strategies if the digital twin needs additional data in order to increase the confidence level of a particular task.

Note that the ability to predict future outcomes, and quantify the level of confidence in these predictions are particularly important features. This is now considered by using an example layout for a simulation digital twin.

2.2 Example layout of simulation digital twin

A schematic representation of a simulation digital twin during an asset management phase of a wind turbine structure is shown in Figure 2. Here, data sets are recorded from the physical twin, and control and scheduling commands fed back as required (enabling supervision and operation). The recorded data (potentially in real-time and from similar or legacy sources) are used for tasks in combination with the numerical model(s) and physical test-bed(s) (which can include further online devices, systems or databases) to give the required simulation capability. The interaction of these different elements is coordinated by a *workflow*, which also provides the user with visualisation and quantitative outputs.

As noted above, the exact formulation of a digital twin is context dependent, and so the elements shown inside the digital twin box in Figure 2 are called the *building blocks* required for this specific context. In this example the building blocks are data sets; control & scheduling; numerical models; physical test-beds; workflow; visualisation; and quantitative output data.

The workflow has a central role in providing all the *required processes* that the digital twin is expected to perform. The workflow must also have a user interface enabling commands to be received from the users, and the quantitative and visual outputs to be provided.

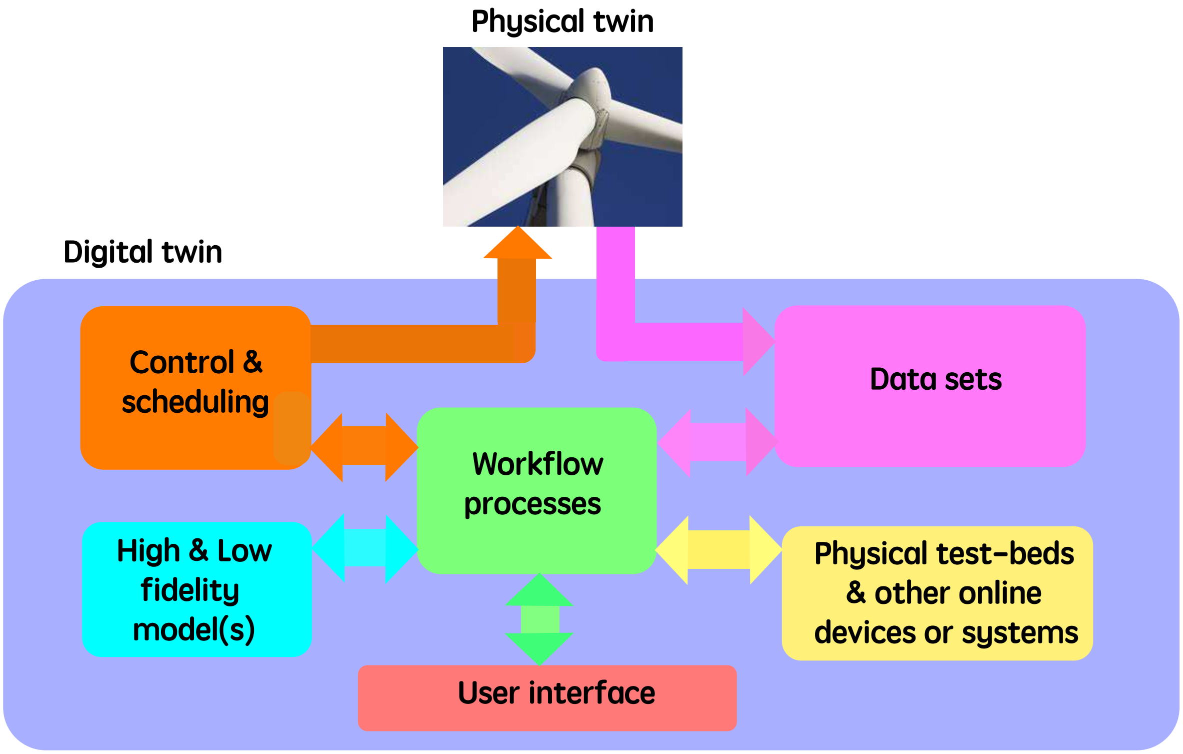


Figure 2: Schematic representation of a simulation digital twin during an assessment management phase, showing the required elements for the simulation-twin and their interrelations.

The workflow will coordinate and sequence the required processes based on the aims and objectives of the digital twin. The required processes themselves can be constructed from a series of "building blocks" within the workflow. The example considered here is of a simulation-twin requiring uncertainty Quantification (UQ), and so it shall be assumed that the required building blocks are:

- physics-based modelling;
- software integration and management;
- verification & validation (V & V);
- uncertainty quantification (UQ);
- quantification of predictive confidence and diagnostics;
- output visualisation (virtual inspection).

In addition to a workflow process related to each building block, it is possible that additional workflow processes can be created by combining and further augmenting these underlying building blocks. For the current example, of a simulation-twin, the process related to data-augmented modelling is now considered.

2.3 Data-augmented modelling

Computer models, regardless of the level of fidelity, are typically not able to capture all possible physics exhibited by an engineering system. As a consequence, a digital twin will augment the outputs from computer models with data to get closer to providing *ultra-realistic* predictions. One way to begin to quantify this is to define the *model discrepancy*. This is simply the mismatch between the computer model output and the measured process from the physical twin (assuming for simplicity there is no observational uncertainty). Two points are worthy of note here. First, model discrepancy it usually quite straightforward to measure (or estimate in the presence of observational uncertainty) even if the physical twin and/or computer model(s) are very complex. Second, even when the parameters are treated as deterministic and considered to be "truly" known, there will typically still be a mismatch, and hence some level of model discrepancy.

Therefore, based on the fact that computer modelling alone will be inadequate, models will be augmented by information from physically recorded data in order to create a digital twin. In fact this augmentation process is one of the core attributes of a digital twin, and for the purpose of demonstrating the concept it will be assumed that the digital twin has just a single computer model. Then, following the approach of Kennedy & O'Hagan [16], the computer model in the digital twin will be represented as

$$\mathbf{z}(\mathbf{x}) = \mathbf{y}(\mathbf{x}) + e = \eta(\mathbf{x}, \boldsymbol{\theta}) + \delta(\mathbf{x}) + e, \tag{1}$$

where $\mathbf{z}(\mathbf{x})$ and $\mathbf{y}(\mathbf{x})$ are respectively the observational and bias (or model discrepancy)-corrected computer model outputs based on the given inputs $\mathbf{x}$. The bias-corrected computer model output is equal to the sum of the computer model $\eta(\mathbf{x}, \boldsymbol{\theta})$ and the model discrepancy $\delta(\mathbf{x})$, where $\boldsymbol{\theta}$ are parameters of the computer model. The observations are assumed to be uncertain, and this is represented in the model by the addition of error, e.

The definitions in Eq. (1) allow us to build a digital twin in which firstly, data sets are used to quantify the model discrepancy, $\delta(\mathbf{x})$. Then secondly, this information is used to add a correction (i.e calibrate) the computer model so that the augmented outputs, $\mathbf{z}(\mathbf{x})$, properly reflect the measured outputs from the physical twin. In the next Section a numerical example of this process will be presented.

2.4 Numerical example

The importance of the model discrepancy term is demonstrated for a simple numerical example; a mass, tension wire system, shown schematically in Fig. 3. The objective is to predict the natural frequency of the system f (in Hz), given different tensions T, where the mass m is unknown. To reflect the concept of model discrepancy it is assumed that the "true" system has an off-centred mass where, L=1m a=0.2m (Eq. (2) and Fig. 3a) and that the "true" mass is 5.45kg. However, the model of the system does not include the ability in incorporate an offset, instead modelling the system with a centred mass, representing a level of missing physics (Eq. (3) and Fig. 3b), we have

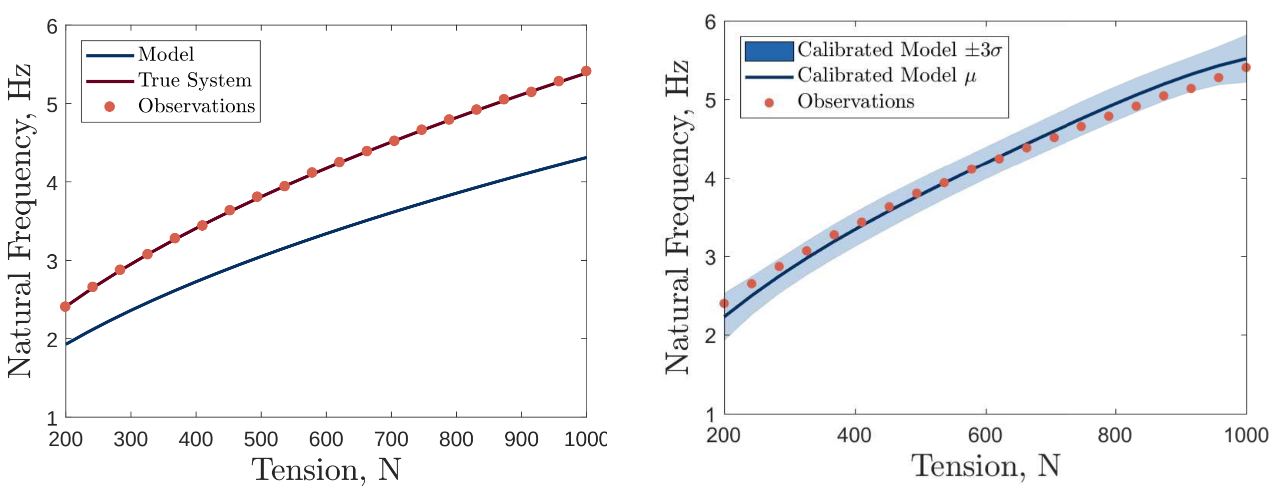
$$f_{true} = \frac{1}{2\pi}\left(\frac{T(a+b)}{mab}\right)^{\frac{1}{2}} \tag{2}$$

(a) (b)

Figure 3: Mass, tensioned wire system schematic. Panel (a) shows the model; centred mass, tensioned wire and panel (b) the 'true' system; off-centred mass, tensioned wire. (L=1m a=0.2m).

$$f_{model} = \frac{1}{\pi}\left(\frac{T}{mL}\right)^{\frac{1}{2}} \tag{3}$$

Clearly when the computer model uses the "true" value of m there will be model discrepancy, as shown in Fig. 4a, where the computer model, true system and experimental observation (with $e \sim \mathcal{N}(0, 0.01^2)$) are compared when $m = 5.45$kg. If calibration is performed (here Bayesian calibration is utilised) without considering model discrepancy the estimated parameter value will be biased and there is no guarantee the functional form of the output will be correct. Figure 4b presents the outcome of Bayesian calibration for the model (with a prior $M \sim \mathcal{N}(5.45, 0.55^2)$) where the maximum *a posteriori* probability (MAP) estimate is $M = 5.01$kg. The result also demonstrates the difficulty in replicating the output correctly as model form errors are apparent (for further examples on the importance of model discrepancy see [17]).



(a) (b)

Figure 4: Mass tension wire system example. Panel (a) indicates the model discrepancy between the model and "true" system when the "true" parameter value is used. Panel (b) presents the results of Bayesian calibration.

2.5 Implications for digital twin technology

It should be noted that the example presented is highly simplified compared to the intended application for digital twin technology. However, the intention is to demonstrate the power of data augmentation applied to models containing unmodelled physics. A more general interpretation of the process is that of grey-box modelling. The grey box model is formed by combining a white box (the physics-based model) with a black box (a machine learning or statistical process) in order to capture model discrepancy.

Without quantifying model discrepancy, parameters inferred during an uncertainty quantification process will typically be biased or potentially "over-confident", leading to inaccurate predictions [17]. In a digital twin where biased parameters at a low-level model are then combined with other augmented models, this may lead to considerable errors at a full-system level. This affect could be compounded in a digital twin which includes multiple models, particularly with modelling issues such as mesh mismatches, which will result in several sources of model form errors, that if propagated to the next model/level will compound further. Trivially, bias will occur in calibrated parameters across the complete set of models, if discrepancy isn't accounted for. As a result, in contrast to the case of a single validated model, it will be essential for digital twins attempting to join multiple models to incorporate mechanisms for inferring and compensating for model discrepancy.

Once quantified model discrepancy should be used to inform model improvements. By interrogating where the largest sources of model discrepancy exist and the functional form of the bias, improvement to the physical models can be made. This aids building confidence in predictions by ultimately leading to a reduction in uncertainty, where the digital twin will systematically improve and evolve over the life-cycle of the structure.

3 Conclusions

In this paper the *building blocks* of a simulation digital twin have been briefly outlined. In order to fuse the building blocks together a series of workflow processes are required, and the process of data-augmented modelling was considered in more detail. This concept is a key defining characteristic of the digital twin idea, and it was shown using a simple numerical example how augmenting a model with data can be used to compensate for the inherent model discrepancy.

There are multiple approaches for inferring model discrepancy, all of which use a data augmentation process, where model form errors are compensated for. The choice of a digital twin does not prescribe a single strategy for inferring model discrepancy, however it will not be possible to ignore this form of uncertainty and bias. General approaches may incorporate grey-box modelling via machine learning components, or fully statistical methods; this is a challenge to the implementation of a digital twin.

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