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The Digital Twin for Engineering Applications

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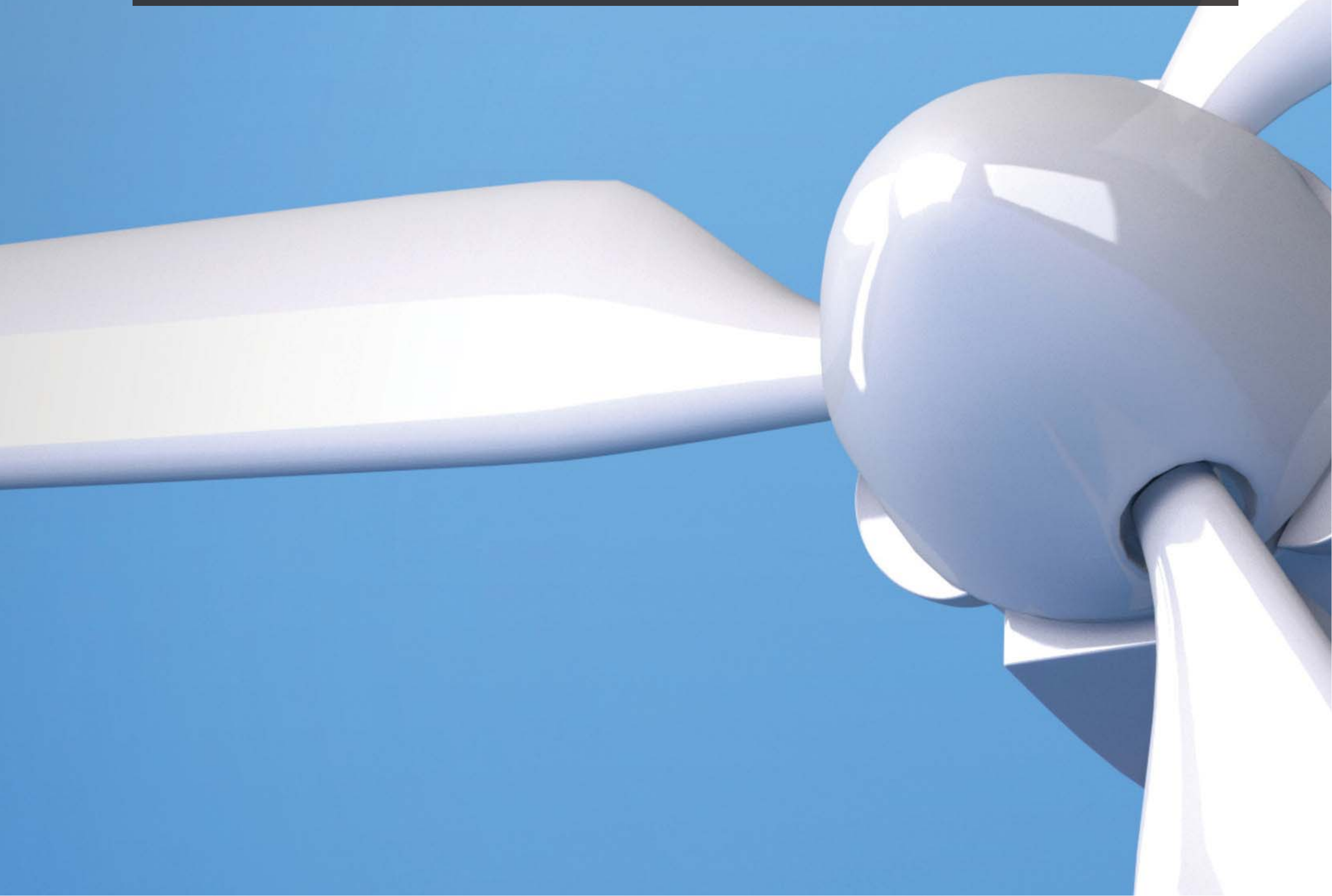
We are living through an era of digital transition. Throughout the media, and increasingly in the workplace, it's common to hear discussion related to "Industry 4.0", "big data" and the "Internet-of-things". These are broad concepts that can often lack specific details of how they might arise in practice, particularly for engineers. However, within this broader landscape, the concept of a "digital twin" has emerged as a potentially transformative idea for engineers engaged in modelling and simulation.



A digital twin is a virtual duplicate of an engineering system built from a combination of models and data. Most importantly, it can be used as a predictive tool to inform key engineering decisions. A good introduction to the idea, including the background and history of the topic, is given by Datta (2017).

The motivation for the digital twin comes from the fact that, in most engineering sectors we are becoming increasingly reliant on computer simulations to help make decisions about design and management of engineering structures. There are numerous challenges relating to this, not least how much trust can be given to any specific simulation result. In many sectors, high-performance computing (HPC) has been applied to try to solve this problem, by building increasingly high-fidelity models in the belief that this would remove uncertainty. Using raw computing power can work in certain cases, but there are a considerable number of engineering problems that still have significant uncertainty associated with simulations even with HPC.

One example is the problem of mechanical joints. As models have achieved higher fidelity, individual components can be more accurately modelled. However, for many systems this has just highlighted the issue of uncertainty in modelling the joints between components in complex structures. These types of effects are typically strongly nonlinear, and localised. To make things even more challenging, systems operating in dynamic environments are highly sensitive to very small changes in (or disturbances to) the structure. For example, small differences in tolerances, joint properties (such as friction), or the operating environment (temperature, humidity), can all lead to large changes in operational performance.

Another example is the fact that modern engineering systems are typically highly complex, and as a result it is common practice to have multiple teams of engineers creating different models of components and subsystems in parallel. These models often have different levels of fidelity, assumptions about uncertainty, and different inputs and outputs. A common scenario is that the sub-system models cannot be unified into a model of the complete system. In addition, there are typically multiple sources (and formats) of data from existing systems, users, control systems, or test results that could potentially be included into the design or operation process.

So what does this mean for engineering simulation? HPC is very likely to continue to deliver performance improvements, but the next transformative step for simulation is to harness the power of data. Use of data has been transforming many aspects of our daily lives, most notably through the activities of companies like Google and Facebook, who have access to large quantities of data from consumers which they use to target advertising and for other applications. Engineering systems have been going through a related data transition, as sensor technology has advanced. Many systems now have the potential to gather huge amounts of data.

The main idea of the digital twin is to combine models and data to create a virtual prediction tool. The obvious question is: How do you combine models and data? There is a long-established historical context. For example, in applications relating to linear dynamics, modal testing has been established as the method for validating models (Ewins 2000, Au 2017). Using this approach, vibration modes are used to connect the model to the measured data. In essence the modal representation can be related to both a physics-based model (typically a finite element model representing the geometric and material properties of the system) and an identification method (or data-driven model). For other applications there are also well-established methods for validating simulation results, and in recent years there has been a strong emphasis on extending all these methods to include nonlinear systems (see for example Hill et al. 2014 and references therein).

A useful framework to use when considering how to create a digital twin is to consider white, black and grey box models (Worden & Tomlinson 2000). White-box models are based on nearly perfect knowledge of the physics, whereas black-box models are derived entirely from measured data, with no assumed knowledge of the physics at all. Grey-box models are a blend of the two, with some knowledge of the physics and some reliance on data - this is the format required for a digital twin. The difference between the digital twin and a validated model, comes primarily from the much more extensive use of data (see as an example Tuegel et al 2011).

There have been previous developments in this area, particularly finite element updating methods, where model parameters are adjusted based on experimental observations (Friswell & Mottershead, 1995). The digital twin will also incorporate this functionality but will typically be expected to be updated much more regularly, ultimately in near real-time. The digital twin will also use a whole range of data-based algorithms, to compare each new data set with those in the database. Monitoring the condition of the structure will be based on an evolving history of information. Machine learning methods, will be foremost among the algorithms used for this purpose (Worden & Green 2014).

To create an interface between the data-driven methods and the high-fidelity finite element models, the digital twin will use a suite of intermediate representations (similar to modes in modal analysis). These will include reduced and/or low order models of the system or

Figure 1: The Concept of a digital twin

subsystems. It can also use numerical-experimental hybrid testing to include test-bed data (Bursi & Wagg 2000). To manage all these interactions, at the core of the digital twin will be a work-flow system, enabling all required processes to be scheduled. Ultimately, machine learning (and associated techniques from the field of artificial intelligence) will enable the digital twin to "learn" the work-flow process based on the information it receives over time.

So, the digital twin is much more than just a validated model. It will be a robustly-validated time-evolving representation of the system, which starts during the design phase, and continuing to evolve during manufacture, commissioning, operation and finally decommissioning. It is a virtual twin of the real system, as it will continually reflect the changes that occur in the structure. Just like weather forecast models, it will continually update from the latest observations, and then make predictions of the short-term future behavior to be expected.

The final important issue is how to deal with uncertainty within the digital twin (Grieves & Vickers, 2017). To inform engineering decision makers, enabling trust in virtual predictions is essential (Atkinson et al. 2011). To do this the trust that can be associated with predictions from the digital twin must be quantified, and for this it is essential to integrate techniques from uncertainty quantification and propagation. This quantification has to be applied to all parts of the digital twin, data, models and processes (as an early example see Li et al. 2017). Where required these quantities should be propagated through the model, to enable engineers to assess the level of confidence they can have about the model predictions (Au 2014).

Of course, there will need to be a user interface to enable interactions with the digital twin. Already there are several software demonstrators that use a CAD, or similar, representation of the system. Connectivity with databases will clearly be important. Here we can see the usefulness of the internet to link the twin with data and other observations as close to real-time as possible. It is likely that many of the methods in the digital twin will be non-intrusive i.e. they will be developed as wrappers without a requirement to modify existing source code or software tools.

The digital twin is a relatively new idea, that has created significant interest in many areas of industry. As engineers are being required to design and manage ever more complex engineering systems, the idea of having a time-evolving digital twin is a highly attractive one. However, there are substantial challenges to address in order for this technology to reach full maturity, and so deliver the potentially transformative developments into the engineering community.

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