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ABSTRACT

A number of case studies are presented which were developed from interviews with industry data science experts.

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THE DIGITAL TWIN

While there is no standard definition, a digital twin can be thought of as a virtual model, or representation, that is the counterpart (or twin) of a physical object and/or process.

The definition above encompases an individual component, product, system or whole facility; depending on the chosen physical scale that the digital twin is to be associated with. The complexity of the behaviour predicted and the required or necessary level of detail will have a large part to play in this.

For a digital twin to be of use, it needs to be capable of predicting behaviour of it's real-world counterpart (or twin). These predicted behaviours could relate to operational performance, efficiency and productivity, it could relate to reliability and integrity; the focus depends on the aims of the digital twin's application. How the digital twins make predictions will depend on the system being considered. Some may use data gathered from sensors to predict or control future behaviour, but often engineers need to understand detail about the system behaviour which cannot be measured directly. In such cases data must be predictied through methods such as predictive engineering.

Primarily this paper seeks to explore the possibilities for use of predictive engineering analytics embedded in the digital twin during the operating life of equipment. The digital twin has a lifecycle that mirrors the actual engineering product or system, and can allow insights into product performance all the way from concept development right through to end-of-life. In this paper the authors will show how design data can be critical to delivering a predictive capability in a digital twin to aid operational performance.

ENGINEERING LIFECYCLE AND THE DIGITAL TWIN

This paper will focus on a small sample of potential digital twin applications with focus on equipment in the operating phase of its lifecyle . However, the data and knowledge that is built up from the first inception of a product, system or facility can be extremely valuable in building a digital twin. Even at the earliest stages of product development, by providing a digital representation of the concept, the digital twin can help optimise and refine the product design - whether a single product, an engineering facility, or an entire oil field development (for example). The data gathered

from a digital twin used to aid or optimize a design could then be used when implementing the in-serivce, or operating, version of the digital twin; this is discussed in a subsea-related case later in this paper.

During the manufacturing process, the digital twin can provide additional information to allow insight into the quality of the finished product – and check that the product will meet the specified requirements - before it is manufactured.

Following installation, the digital twin can provide continued insights into the performance of the equipment throughout its operational life – crucially, to verify the operational integrity or performance throughout its operational life, which, in the oil and gas industry, can extend into 20, or 30 years in longer field-life scenarios.

THE DATA-DRIVEN DIGITAL TWIN FOR OPERATIONS

With regards to a digital twin in the context of an operating system take, for example, a subsea production tree on the seabed; used to control flow from, and provide access to, a subsea well. These complex engineered systems have a wide range of requirements, functions and capabilities.

While the system is in operation, sensors enable operators to stream data from the seabed – measurements from flow meters, temperature sensors, pressure transducers and sand monitors for example. Large amounts of data may be generated from the sensors, but the data must be curated in order that it may be analysed to provide engineering insight. The scale of this data curation task, if not appropriately planned, is often an underestimated element in both the application of data science and when building the digital twin. It becomes an operational challenge to gain insight from the data produced.

When the datasets are in an accessible format for analysis, we can begin to understand and use it, to learn and to inform operating decisions. Such decisions could be for controlling the production rate, or the system itself; to help understand or plan maintenance, to aid flow assurance or perhaps to improve the efficiency or operation of a particular system.

PREDICTIVE DIGITAL TWIN FOR PERFORMANCE AND INTEGRITY

Figure 1 Operating digital twin flow of data and information

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There are many situations where the data required to make engineering decisions may be unavailable. For example, we may need to know temperatures, pressures or erosion rates at a location where no sensors are positioned. Equally, sensors cannot measure future events. Minor unexpected operating conditions, continuing for extended periods, have the potential to impact a system's efficiency or maintenance requirements, while extreme

events can significantly impact the integrity or opee the pot 41 e036 34i658 miG of 34i658 miG of 34i658 miG o \$5 k97384 (0 0 10 36 3170135]

Figure 2 Operating digital twin flow of data and information including predictive data generation

PREDICTIVE DATA THROUGH SIMULATION

'Predictive engineering analytics' is the application of multidisciplinary engineering simulation, coupled with intelligent reporting and data analytics. Intelligent reporting and data analytics refer to how data is used and processed.

In engineering endeavours one can view simulation as the application of science-based models to predict real-world

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approaches to solving engineering problems. It is unlikely that a high-fidelity model will generate new data in real-time, and this is where the next levels of simulation become more appropriate in many cases.

SYSTEM SIMULATION

System simulation is an approach using a reduced level of geometric detail than high fidelity approaches. System simulations usually employ one- or two-dimensional representations of a system, still often using the fundamental scientific laws and equations of a real-world behaviour, but with lower geometric resolution, fidelity and detail. This approach typically requires less computational resource than a high fidelity approach of the same system, and therefore less time to render the simulation solution and lends itself well to quicker solutions and larger system-level predictions.

Taking the example of a subsea production system, with a subsea jumper connecting a production tree to a manifold system. In Figure 3 below the jumper is shown in three-dimensions in a highfidelity CFD simulation (left) and in a system simulation (right) below, both are being used to predict thermal behaviour.

The system comprises mainly insulated pipe with some exposed locations (cold spots) at lifting points and sensors. The jumper connects to the production system at each end with geometrically (and thermally) complex connectors. To understand the thermal behviour of this jumper (and connectors), there is a need to predict the temperatures at many different locations. We may use the temperature predictions to assess the risk of hydrate formation during production or in the event of a system shutdown.

A high fidelity CFD simulation will use a 3D geometrical representation, allowing a very detailed view of the thermal distribution to be predicted throughout the jumper, but it will

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REDUCED ORDER MODELS

Reduced Order Models (ROM) refer to a variety of techniques used to reduce the computational complexity of mathematical models in numerical simulations. At the lowest level of detail, fidelity and computationl resource, ROMs are often not based on fundamental scientific principles, instead they are commonly based on a mathematical description of a system that has been tuned or trained to match known real-world behaviours within a specific set of bounding or operating criteria. This tuning, training and validation is often obtained from validated higher fidelity simulations, test or operational data. Typically ROMs are low fidelity approximations, or reductions, of a system, usually used to predict specific behaviour of a system, or parts of a system in real-time.

A ROM can be created in multiple ways. The simplest ROM is perhaps a curve showing how two variables respond to one another to define a behaviour at a given location (perhaps changing temperature at a point in a system). As the number of input or output variables increase a response surface may need to be generated, where we again feed data on how a system responds and then look up that data when it is is needed. Alternatively, a simple mathematical (or sometimes science-based) model can be created, for example, describing system behaviour using a set of differential equations, characterized by the number of parts of a system and a number of coefficients that need to be trained, tuned and validated to predict a specific system response.

ROMs are the least versatile and flexible of the predictive approaches discussed here, but are the quickest and least resource intensive. They rely on the higher fidelity approaches (or physical data) from which the data can be used to build the reduced order model.

EXAMPLES OF THE PREDICTIVE DIGITAL TWIN

The following examples demonstrate how each of these simulation techniques can be used, and how they need to be brought together with physical data to generate the predictive element of a digital twin for operations, to provide valuable insights.

HEAT EXCHANGER INTEGRITY – THE PREDICTIVE ELEMENT

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The first example looks at the integrity management of a heat exchanger, common to many production and process facilities, as shown in Figure 5.

Figure 5: Shell and tube heat exchanger

The heat exchanger comprises a bank of looped tubes through which steam is passed and which exits the tube bank having transferred its heat to the operating fluid contained in the surrounding vessel.

In this case temperature sensors were reporting excessively high

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temperature gradients. This temperature data was then used in a FEA simulation

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Figure 8 Correlating temperature-stress data at key locations

FIigure 9: Validation of the reduced order model

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In operations, this works by taking the sensor temperature time history data and running this through the reduced order model. The ROM generates the stress response time history and an updated fatigue life which can then be used to calculate a remaining life, this process is shown in Figure 10. This new insight into the system can be used to inform operational cycles and maintenance schedules.

In this way, we have operational temperature data that creates a summary of the structural integrity of the system in real time, this process is demonstrated in the figure below. Extending this concept further, beyond the understanding of the current state of the equipment, the ROM can be used by engineers in operating roles. Engineers, or even an algorithm, can explore and plan how to operate the heat exchanger in the future, based on operating requirements and planned maintenance schedules.

One aspect that the above approach cannot capture, or solve, is the maldistribution of the flow causing the potential integrity risk, perhaps better use of simulation at the design phase, or even design modification would be worth considering.

Figure 10 Reduced order model inputs and outputs

such systems, whether relm $\frac{1}{2}$ ath a-41 $\frac{1}{2}$ denoted by $\frac{1}{2}$ (enoted by $\frac{1}{2}$ denoted by $\frac{1}{2}$ Figure 11 How high-fidelity CFD simulation informs quicker system simulations and reduced order models (ROMs)

B d a e abe e a ROM

For some engineering systems, a system simulation may often be built without the need to train or tune it using higher fidelity approaches; it depends on what is required to be taken from the data obtained and the system complexity. For geometrically or operationally complex engineering systems, a system simulation may need to be trained to obtain accurate data.

In this example four different cases are simulated using the CFD approach as shown in Figure 12, these show temperature of production fluid at a given sensor location in the event of production shutdowns from different flowing temperatures (prior to shutdown). From those high-fidelity simulations, the regions where the key hydrate risks are located can be identified, and detailed temperature data gathered of how the whole system is behaving, both during production and following a shutdown as the system cools.

The first of the four CFD cases was used to train the system simulation; in this case it was used to tune local heat transfer coefficients and thermal characteristics where complex geometrical features exist in the system or insulation designfi

In addition, a digital twin that can predict performance, and understand historical performance, delivers the opportunity

www.element.com/digital-engineering | contact.us@element.com | +44 (0)1332 348844 | The East Mill, Darley Abbey Mills, Derby, UK