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Digital Engineering

PREDICTIVE DIGITAL TWIN FOR PERFORMANCE AND INTEGRITY

WHITEPAPER

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ABSTRACT

The concept of the digital twin can be thought of as a virtual representation of a physical product, engineering system or facility.

This paper presents the role of predictive engineering analytics, alongside operating data, in the digital twin. Using case studies, the authors demonstrate how predictive approaches can be developed to provide data where it cannot be measured and predict future operating data to improve performance, life and integrity of equipment, systems and facilities.

The digital twin is fundamentally based on data, larger datasets provide greater insight. Sensor and inspection data are critical. However, there are scenarios in which engineers require data where it cannot be measured or requires data that cannot be measured. Engineers require ways to extract this data, this can be done through predictive engineering analytics. Predictive engineering analytics, in the form of science-based simulations, combines multiple approaches, often based on fundamental principles of physics and engineering. This paper will demonstrate how high-fidelity approaches, such as Finite Element Analysis (FEA) and Computational Fluid Dynamics (CFD), combined with system-level simulation and reduced-order modelling can work together with field data to provide this data in real-time.

Two case studies presented show how combinations of different levels of science-based modelling approaches can help. A subsea thermal digital twin demonstrates how high-fidelity simulations, undertaken during system design, can be the foundation for reduced order system models capable of capturing critical thermal performance in real time; aiding hydrate risk management during operation. The methods used to train the real-time predictive approach are demonstrated. The second case presented focuses on structural integrity of a heat exchanger showing how real-time sensor data can be translated into structural integrity data and insight through simulation. The cases presented demonstrate the value of science-based predictions to generate data that cannot be obtained from operational sensor data alone. The authors aim to show how the predictive element of the digital twin can be first generated during design and evolved into real-time predictive approaches that provide operations with data that cannot be gained from sensors; when and where it is needed.

Digital twins typically use physical data, limiting operators of in-field equipment to make operational decisions based on information from sensor locations and historical data alone. This can limit assessment of operational performance and integrity of complex production and process systems. In this paper the authors aim to show how, by combining predictive approaches, at differing levels of fidelity and based on fundamental scientific principles, it is possible to generate the missing data required , in both space and time. This can inform and guide operations; filling the gaps where and when physical data is not available.

INTRODUCTION

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

In the development of engineering products and systems, data is generated from initial conceptual ideas, through phases of design, and then through manufacture into installation and operation. How digital technologies are used to create, store, share and use the data has developed significantly in recent decades and in this time the concept of a digital twin has developed.

With increasing access to, and developments in, digital technology the concept of the 'digital twin' has evolved and is discussed, if not yet often used, in many facets of engineering. However, the digital twin remains a relatively new concept, the value of which is not commonly being gained.

Data is generally considered in terms of a discrete moment in time – the product, for example, at a particular stage in its lifecycle. This limits the possibilities and usefulness of the digital twin which, in fact, has a lifecycle that reflects its counterpart, the product itself.

Data is generated at every stage of a product or system's life. This data can be used to embed predictive capabilities within the digital twin, which in turn can provide valuable insights – for example, the capacity of a system to withstand a critical event – throughout its operational life.

In this paper the authors will explore the value of building a predictive capability in the digital twin; using science and mathematics-based approaches capable of predicting real-world behaviours of equipment and systems.

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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 lifecycle . 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.

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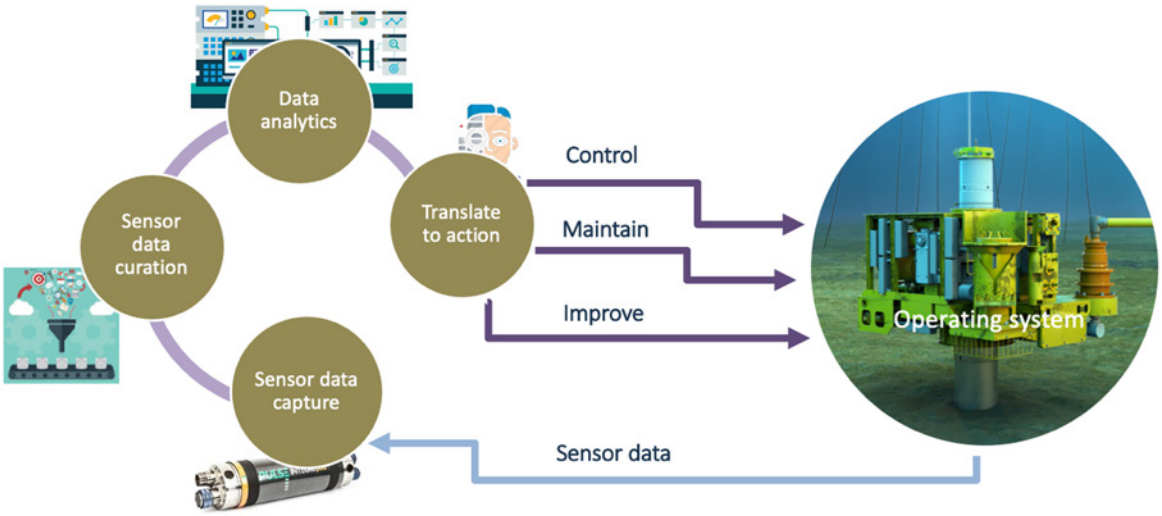

Figure 1 Operating digital twin flow of data and information

Filling in the data gaps

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 operating life of the system.

To predict system behaviour at a point in the future, or evaluate whether a system has the capacity to continue operating safely beyond design conditions, requires more than the existing dataset, which details how a system reacts to a known operating envelope. Similarly, data from sensors alone, which may be in the form of raw data such as sand flow rates, is not sufficient to predict mechanisms such as erosion.

Data beyond that supplied by sensors (and from design data) is required to generate a digital twin. This could take the form of data from conditions or locations that are unable to be measured as well as having the ability to transform raw data measured from the field into engineering insight for example transforming sand flow rates into erosion rates. Generating the data that is unavailable or cannot be extrapolated through historical or design information is often a challenging aspect of building a digital twin.

DIGITAL TWIN FOR OPERATIONS – INCLUDING PREDICTIVE ANALYTICS

A complete digital twin of an operating system must include the ability to predict behaviour in the future. To build a digital twin, one needs data from the field, and the ability to curate and translate that data into meaning, which can then be combined with predictive aspects to inform decision-making. With this data available, operators and engineers gain a deeper understanding of the system, from which operational decisions based on engineering judgement can be made.

This analysis and judgement, may be made by humans, artificial intelligence, machine learning algorithms, or perhaps all three working in concert to translate the data into insights that can support confident decision-making for control maintenance, for example, or system improvement.

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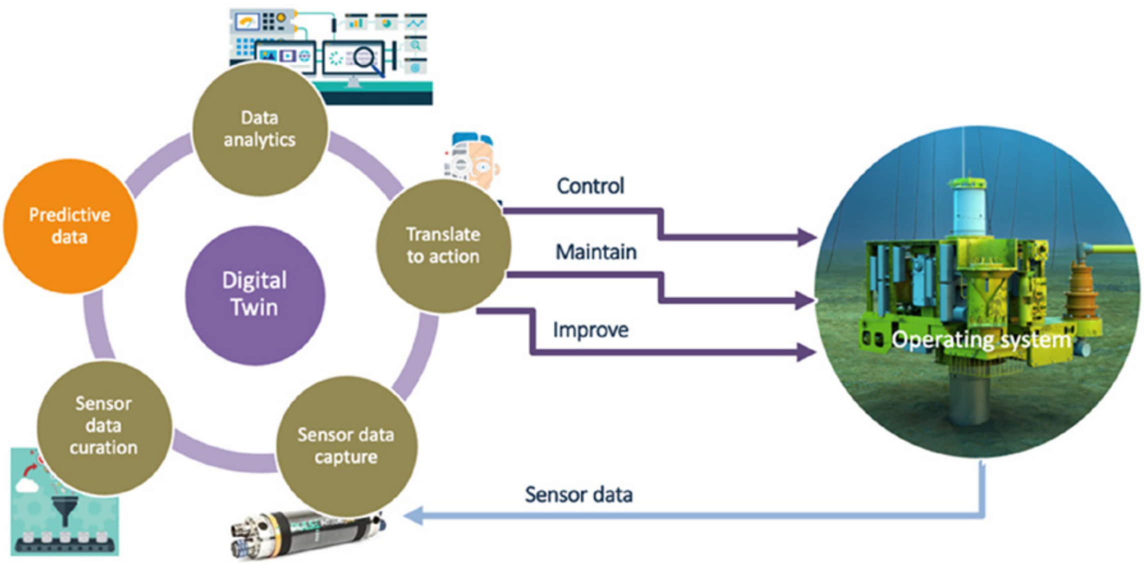

Figure 2 Operating digital twin flow of data and information including predictive data generation

PREDICTIVE DATA THROUGH SIMULATION

'Predictive engineering analytics' is the application of multi-disciplinary 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 behaviours, of equipment or of complete systems. Examples might be flow simulation based on Navier-Stokes equations, structural simulations solving the stress or deformation of a system under load or perhaps electromagnetic behaviours and phenomena governed by the Maxwell equations. Rather than relying solely on data analytics from field measurements, science-based approaches need to be incorporated.

PREDICTIVE DATA GENERATION - APPROACHES

Most real-world physical behaviour can be simulated – such as fluid mechanics, heat transfer, electrical behaviour, acoustics, vibration, chemical or structural response – using equations and modeling techniques that draw on fundamental scientific principles.

The scientific models themselves are not the the vital components described in thie section, instead it is the different ways in which we can use simulation, the different types and methods available to us, that open up different avenues for understanding, and predicting, the behaviour of products or systems as part of a digital twin.

We can think of simulation at different levels; each providing a varying level of detail, or fidelity, to meet the needs of differing real-world applications.

HIGH-FIDELITY SIMULATION

Using geometrically accurate representations of a system or component (often in three dimensions but could be two dimensional or axi-symmetric representations) provides the highest fidelity, and most detailed insight and detail, into the behaviour of the system-be it flow, structural behaviour, heat transfer, electrical behaviour or, electromagnetic (or other) behaviour.

At this level of detail, simulations have the capacity for predicting complex behaviours using the fundamental governing equations of the physics, or other science, considered –tools like CFD, FEA and Discrete Element Methods (DEM) are examples of high fidelity simulation approaches.

In order to provide this level of detail and insight, high fidelity simulation tools are usually, necessarily, computationally the most resource intensive of the levels discussed here; they require the most computational processing resources. However, they provide the most flexible and the most comprehensive 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 high-fidelity CFD simulation (left) and in a system simulation (right) below, both are being used to predict thermal behaviour.

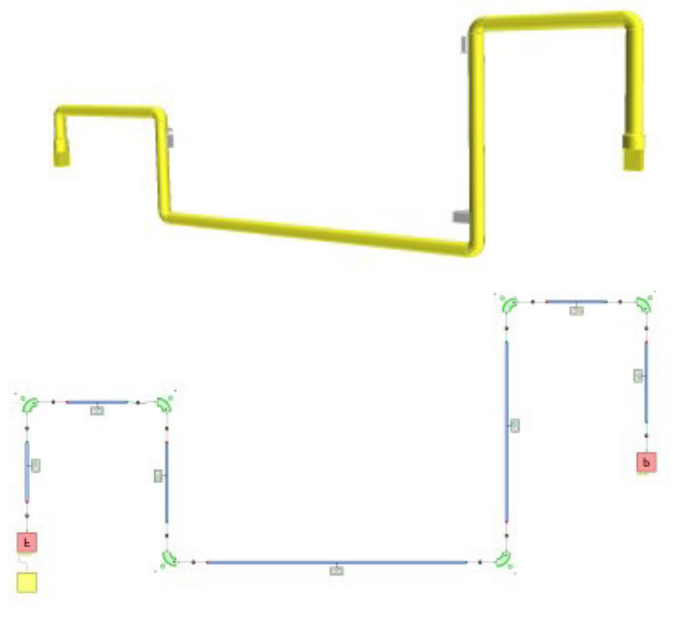

Figure 3 Representation of a subsea jumper in a high-fidelity CFD simulation and system simulation predicting cooldown

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 shut-down.

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 take longer than a system model. A system simulation will give us a profile of temperature at points along the jumper but will not fully resolve areas of highly complex geometry or complex flow and thermal phenomena. For example, the detailed CFD simulation shown above can generate temperature distributions through the whole of the pipe, with an example of details shown in cross section in Figure 4. Whereas the system simulation provides single point data at the monitored location or locations.

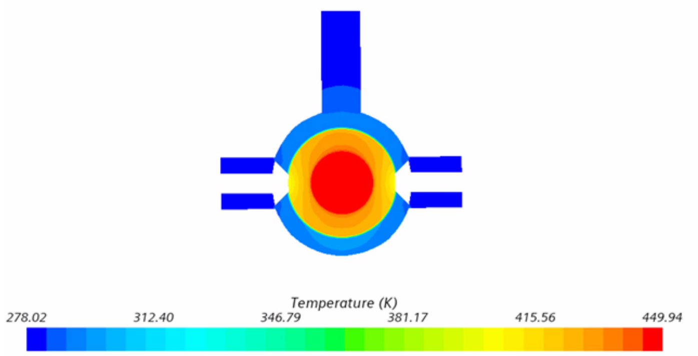

Figure 4: Thermal distribution through a cross section of a subsea jumper

If a detailed understanding of the three-dimensionality in the flow and thermal distribution is needed, then high fidelity simulation is required. However, if all that is required is data at points along the system, in one or two dimensions, then resources and time can be saved by using system simulation techniques. This does assume, however that we can accurately capture the overall system thermal behaviour, to the required accuracy, using the system-level approach. This may need to be confirmed, validated or even trained through high-fidelity simulation or testing.

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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

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 temperatures in some locations causing concern that the thermal gradients could generate stresses and fatigue issues that risk failure of the heat exchanger pipes.

During operation only temperature can be measured in the system, with measurements limited to temperature sensor locations, however more understanding of the system and ultimately understanding of the cause of the excessively high measured temperatures is needed.

Detailed insight from localised temperature data is required. For this, predictive engineering analytics can be used, in the form of simulation, in a number of ways.

Firstly, high fidelity CFD simulation was applied to predict flow distributions, detailed temperature distributions and heat transfer to get a complete picture of the system behaviour as shown in Figure 6. This identifies an issue with flow distribution entering the heat exchanger tube bundles and causing excessive

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temperature gradients. This temperature data was then used in a FEA simulation as shown in Figure 7 to assess the operating life of the system, obtain the stress history experienced and predict the impact of the temperature gradients on the life of the equipment.

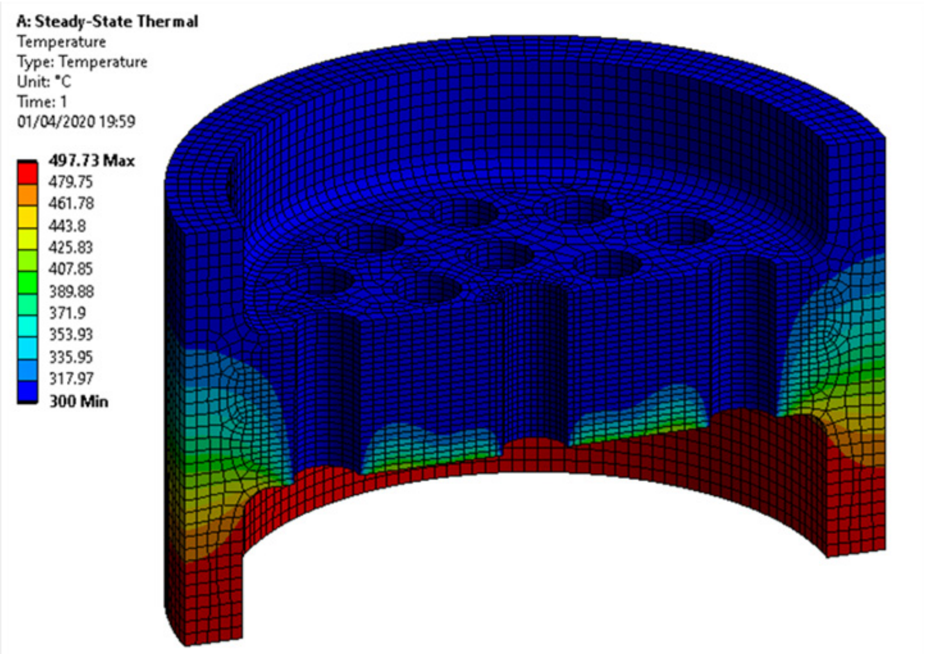

Figure 6: Flow and thermal model of shell and tube heat exchanger (CFD)

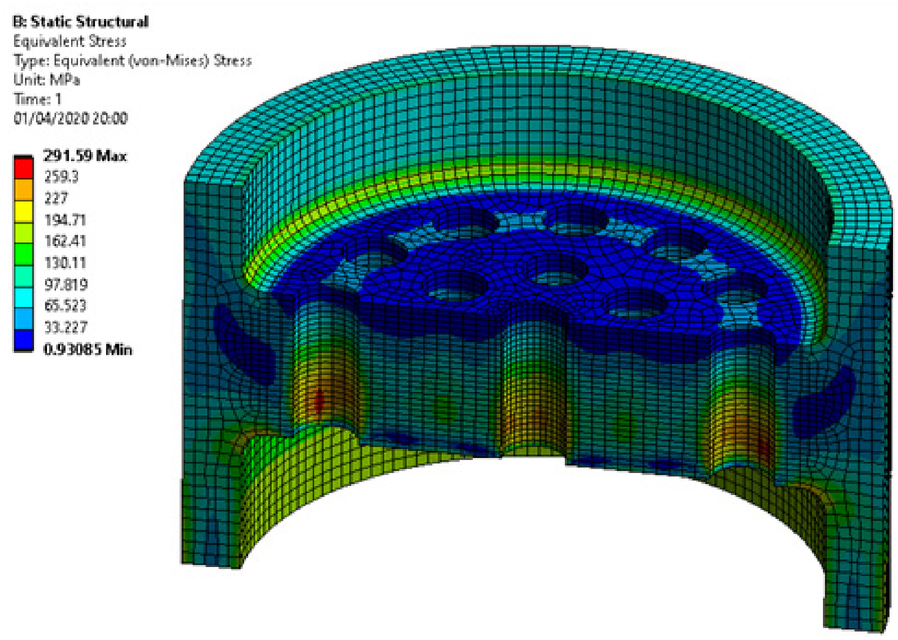

Figure 7: Thermal and stress model of a shell and tube heat exchanger (FEA)

But using this approach to assess the whole life of a system like this can take significant time, and the operating history and the operating life of this equipment is long and complex. In such circumstances the high fidelity approach is usually too time-consuming to assess the complete operating life alone. Instead, using the data generated to build a ROM, and training or educating it to allow us to predict the relevant data much more quickly.

Building the Reduced Order Model

Taking the temperatures from the steam bank (i.e., the tubes), gives an understanding of the flow distribution using a CFD simulation and we can model the stress distributions for a small set of cases for which operating data is available using FEA. This approach was validated using known operating conditions and measured temperature data by comparing the predicted and actual system behaviour. Using this data, operating conditions were correlated to a stress response, using FEA as shown in Figure 8. This insight was used to identify the locations critical to the system's integrity.

By drawing correlations between the operating conditions and temperatures at sensor locations with stress predicted at the identified critical locations in the system, a ROM was generated and trained to match the system behaviour. Figure 9 shows the strong correlation between the data sets generated by the high fidelity FEA simulations and the ROM. This provides the basis for gaining quick operational insight as the ROM runs in realtime.

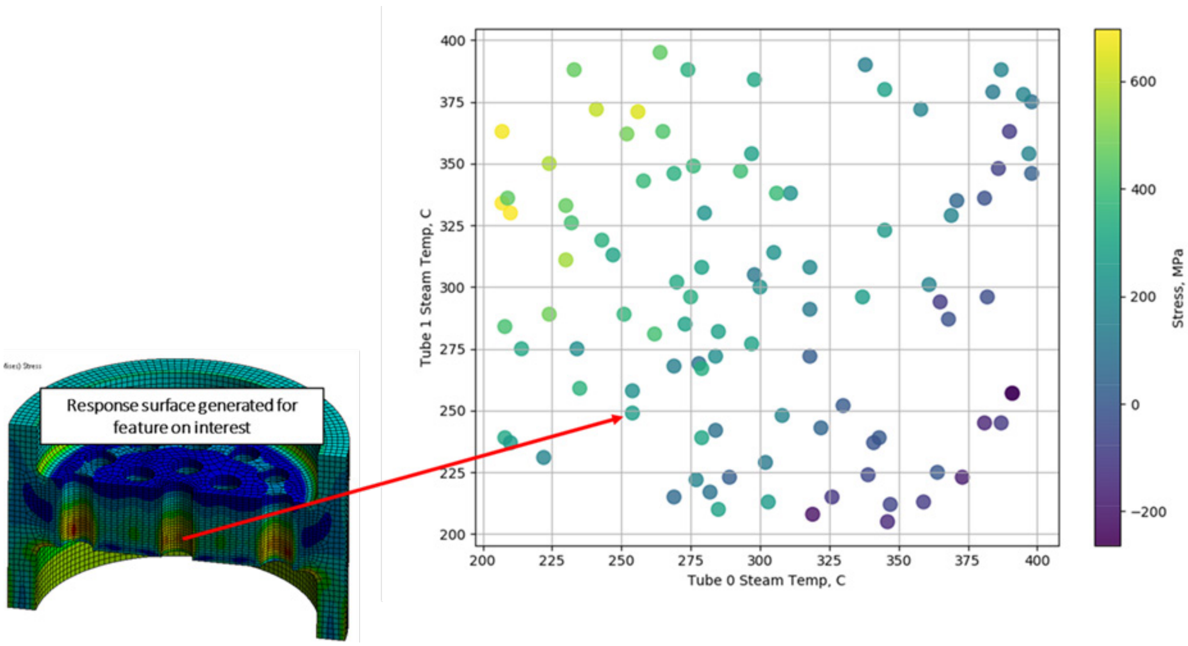

Figure 8 Correlating temperature-stress data at key locations

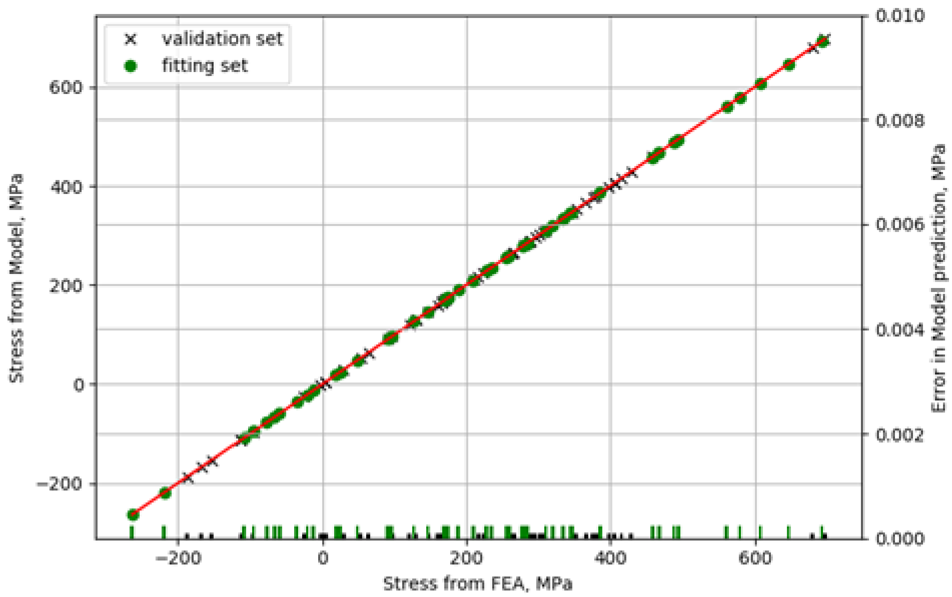

Figure 9: Validation of the reduced order model

Application of Reduced Order Model into operation

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.

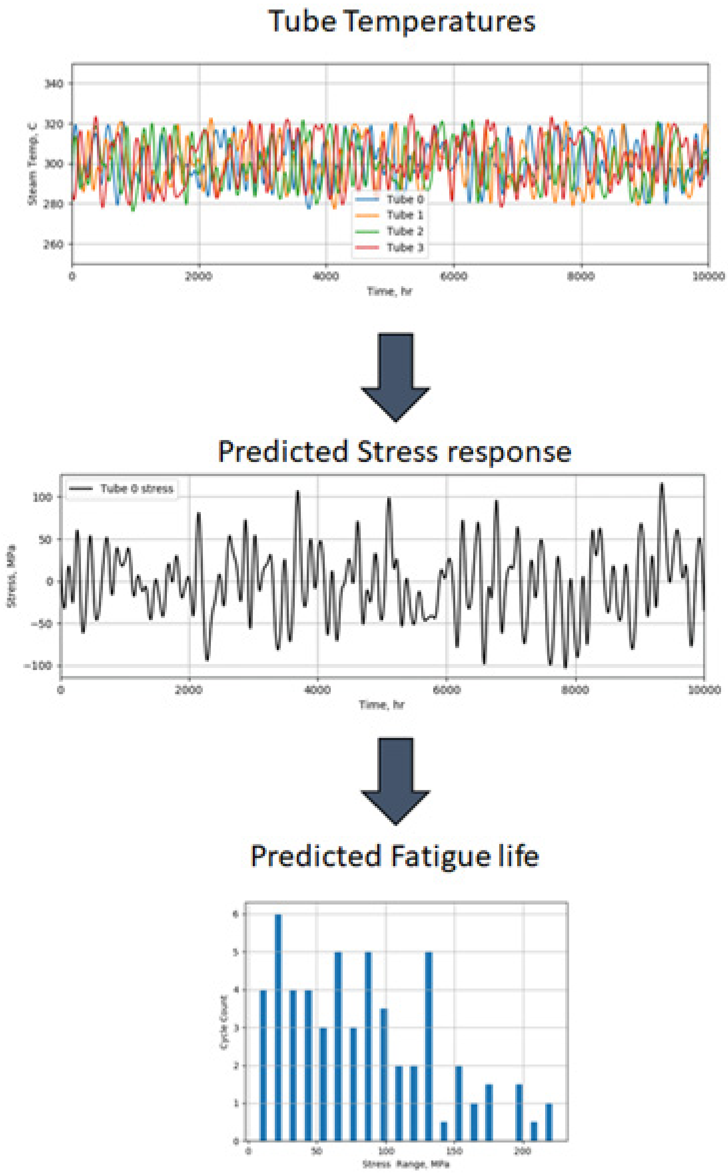

Figure 10 Reduced order model inputs and outputs

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SUBSEA PRODUCTION - THERMAL MANAGEMENT

Thermal management is a key aspect of any subsea production flow assurance strategy. This may be driven simply to maintain the required operating conditions between the reservoir and production facility, or by the need to manage the hydrate formation risk. In many subsea production systems, this risk is related to the composition the of the fluids produced, the operating temperatures, pressures, and system configuration and design. Accordingly, understanding thermal performance of such systems, whether reliant on passive or active insulation or even if uninsulated, is critical to successful and reliable production operations.

CFD is a high fidelity approach commonly used to aid design and to validate the thermal performance of subsea systems. However, the complex and resource intensive nature of this high-fidelity simulation approach is not conducive to delivering insight in real time during operations.

When introducing the concept of system simulation, the subsea jumper was introduced, which is essentially a pipe connecting a production tree (used to contract flow from and access to a subsea well) and a manifold system (connecting multiple wells). This is a highly three-dimensional system, in this case insulated to support thermal performance but with multiple coldspots and complexities such as the lifting points, temperate sensors and sand detectors and the connection systems at each end. To confirm that the system is designed to offer optimal thermal performance, CFD is often used to assess the jumper at a single worst case condition, but this offers little information about the thermal performance in operation away from this design condition.

Modelling approach

With the subsea jumper installed and operational, it is common to use the design performance, checked against a single design condition, to drive operational decisions like the time available before starting hydrate mitigation measures, following a halt in production (no-touch period). However, operational conditions will vary significantly from design conditions. In the event of a halt in production, the operating conditions could vary compared to the single design point considered. This would produce a different thermal response from the system, leading to different time from stopping production to risk of hydrate formation. Knowing how much time is available before hydrates form could help to form operational decisions.

When any engineering facility is operational, data is often needed in real time and it needs to be available in a manner that can enable engineering decisions. As the previously detailed heat exchanger example showed, temperatures alone could not provide detail about the integrity of a system. Limited temperature sensor readings were being converted to a full temperature field, which was used to predict the stress history before the remaining life of the system could be predicted; this is the insight required, and which was delivered by the predictive element of the digital twin.

In the case of the subsea system, high fidelity simulations used in design cannot meet the requirement of delivering insight in real-time. In this case we turn to system simulation to deliver real-time insight.

Using system simulation, a model of the subsea jumper that represents the high-fidelity model can be built, just in lower fidelity as shown in Figure 3. The advantage of the system simulation approach is that use can still be made of fundamental scientific principles and solving the physics of the system (like in a high-fidelity approach) just with lower resolution. This enables us to predict temperatures throughout the system and across a wider range of scenarios than would be possible with a mathematical ROM, whose range of applicability extends to the data-set used to build it i.e. it relies on being informed by science-based models or physical data.

In the case of the subsea equipment, high fidelity models are still required to help train and verify the system approach. High fidelity CFD models are capable of predicting temperatures accurately at all locations in the system and can be used to tune and verify the system simulation; for example to account for complex design details or phenomena and their impact on thermal response at critical locations. The process is shown schematically from CFD simulation to system simulation or ROM in Figure 11.

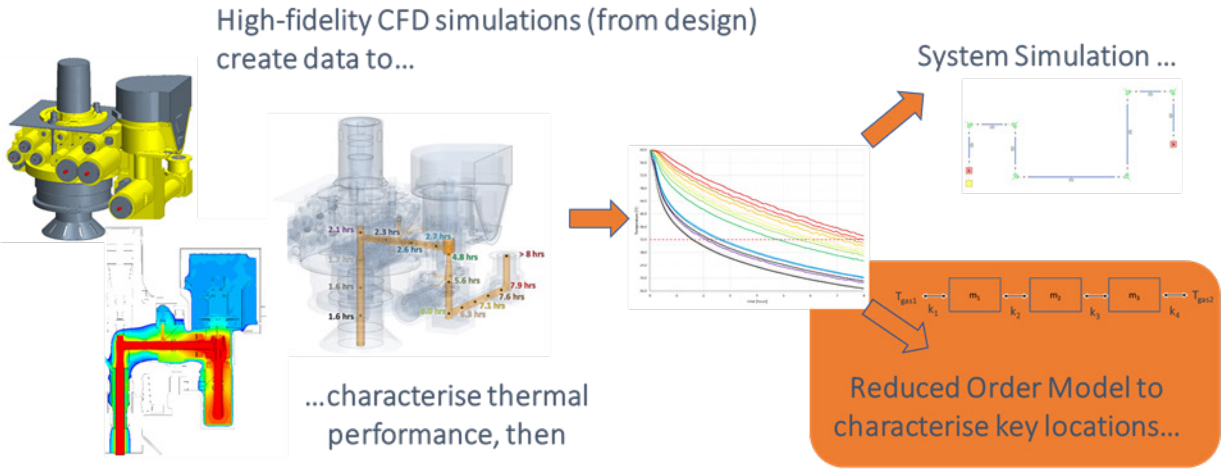

Figure 11 How high-fidelity CFD simulation informs quicker system simulations and reduced order models (ROMs)

Building a reliable system simulation or 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 design. Using this training data, the other three cases were used to validate the system simulation to ensure it was able to predict temperatures accurately across all the conditions the equipment may experience.

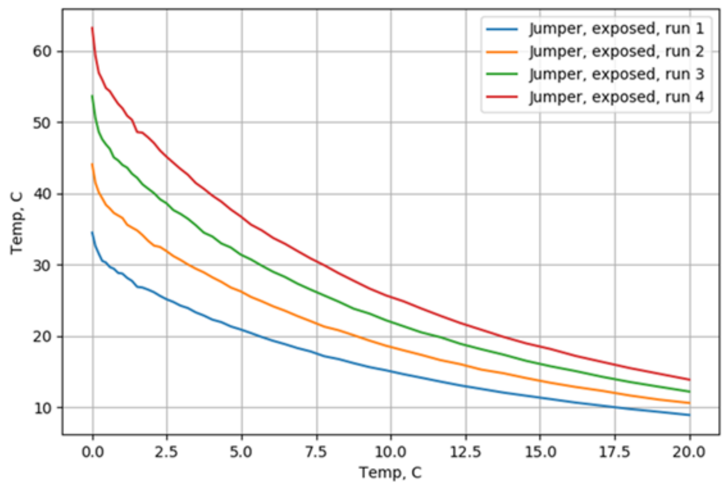

Figure 12 High-fidelity CFD data used to build the system simulation or ROM

Figure 13 below shows the CFD cool down data and the prediction using the system simulation at one location where a geometrical feature exists in the first case. In the left hand chart some differences between the two temperature-time plots can be seen. By tuning the local heat transfer coefficients and thermal properties the system simulation was tuned until the data sets correlate well. The right hand image in Figure 13 demonstrates how both the CFD and system simulation data fall on top of each other to provide the benchmark case one.

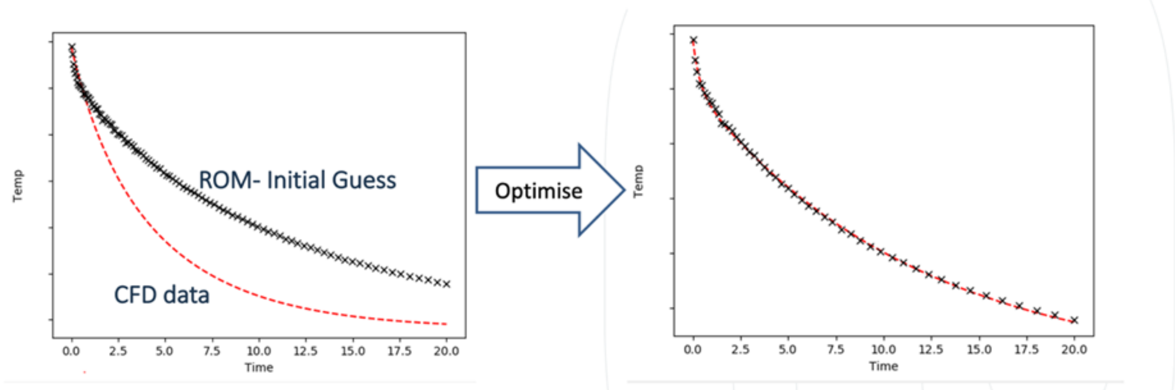

Figure 13 Training the system simulation or ROM using optimisation

When the same tuned system simulation was applied to the remaining three cases, an excellent correlation can be as shown in Figure 14. –In the figure below we present temperatures at a single location for cases 2 to 4, in each case the brighter coloured line is the system simulation and the darker line CFD data. Very good agreement is gained across all locations between CFD and system simulation data. This same correlation is obtained at other locations through the system. In this way the transient thermal response of the complete subsea jumper was captured, and the system simulation provides a real-time prediction of the temperatures allowing risk of hydrate formation to be assessed.

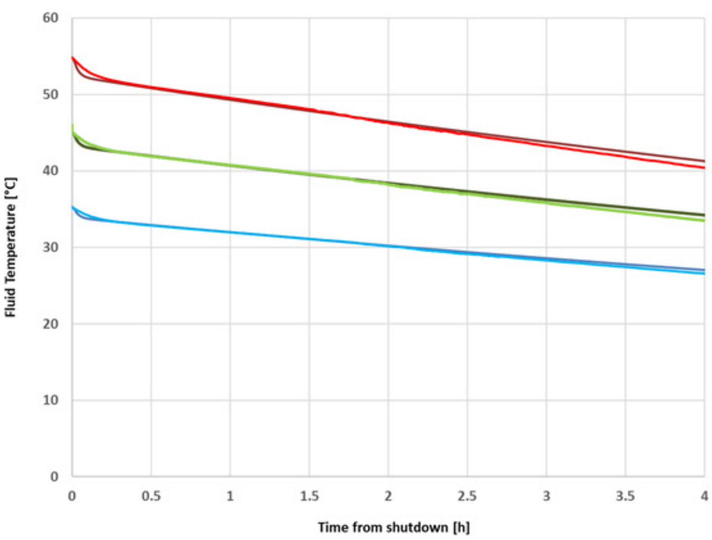

Figure 14 Comparisons between high-fidelity and system simulations after training for 3 cases

To summarise: a high fidelity simulation was used to create a real-time system simulation capable of informing hydrate formation risk – and this can be embedded very simply into the digital twin for operations, enabling operators access to a hydrate avoidance strategy that lives alongside the changing operating conditions, giving confidence to critical flow assurance decisions. Here we show how tools and approaches used to aid design can be further extended to support operational performance through the digital twin for operation.

CONCLUSIONS

The digital twin offers operators a major step-change in how systems can be operated and maintained by delivering real-time insight into the efficiency, integrity and reliability.

In addition, a digital twin that can predict performance, and understand historical performance, delivers the opportunity for engineers to look to better-understand and manage future operational scenarios.

Like any real-world engineering product or system, the digital twin has a lifecycle. Data can be generated from our very first ideas about a concept and its feasibility, through detailed design, through manufacture and into operation. And if data is generated, it should be captured and used to inform and help engineers in the next phase of the lifecycle; here we aimed to show how simulation data, as often generated in design, can be used to deliver value in a digital twin for operation.

Delivering maximum value of the digital twin through the product lifecycle is about more than technical capability and technology; it will require a new dynamic in how traditional supply chains work together. Operators, equipment designers, the technology developers and engineering service providers must work together in closer collaboration throughout the engineering life cycle.

Whilst this paper has looked at just a small number of applications, it's very easy to see how this concept can be applied in many different aspects of operational engineering – from integrity management through to production efficiency and environmental performance improvements to safety and risk management.

The different types of simulation discussed here (from high fidelity to system simulation and reduced order models) each have specific benefits and each provide value depending on the situation or scenario considered. Indeed, as demonstrated here, the greatest value is gained by using a combination of predictive techniques. The most appropriate technique to use depends upon where you are in the lifecycle and the data you need.

Similarly, whilst predictive engineering analytics provides data and insight, it needs to be coupled with field and test data. Neither can work alone if you are to obtain the full value of the digital twin.