DIGITAL INDUSTRIES SOFTWARE

Data-driven operation with the digital twin

Using predictive engineering analytics in the digital twin for operations

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Introduction

In engineering products and systems development, manufacturers continue to generate data from their first conceptual ideas to the design, manufacturing, installation and operation phases.

The concept of the digital twin has evolved and is used in many engineering facets with the increase in sophisticated developments of digital technology. However, the digital twin of a product is traditionally considered in terms of a discrete moment in time at a particular stage in its lifecycle. This limits the possibilities and usability of the digital twin, which has a lifecycle that reflects its counterpart (the product).

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

This white paper will explore the value of building a predictive capability in the digital twin and describe science and mathematics-based approaches that can predict real-world behaviors of equipment and systems.

The digital twin

What is meant by the term digital twin?

A typical definition is a virtual model or representation that is the exact counterpart (twin) of a physical thing. This thing can be a single object, an entire system, an engineered product or a whole facility, depending on the scale that you want to work at with the digital twin.

Primarily, this white paper seeks to explore the possibilities for using predictive engineering analytics embedded in the digital twin during the operating life of equipment. However, it is important to understand the digital twin has a lifecycle that mirrors the actual engineering product or system and can provide insights in product performance from concept development to end of product life.

The lifecycle of the digital twin

Even at the earliest stages of product development, the digital twin can help optimize and refine the product design — whether it is a single product, an engineering facility or an entire oil field.

During the manufacturing process, the digital twin can support virtual manufacturing to provide insight into the quality of the finished product and be used to verify the product will meet specified requirements before it is manufactured.

Following installation, the digital twin can provide continuous insights into the performance of the equipment throughout its operational life. It enables manufacturers to verify a piece of equipment's operational integrity, which, in the oil and gas industry, can extend to 20 or 30 years in longer field life scenarios.

The digital twin for operations

Looking at the digital twin in the context of an operating system, here is an example of a subsea production tree on the seabed. A subsea tree is used to control flow and provide access to a subsea well. Subsea trees are complex, engineered systems with a wide range of requirements, functions and necessary capabilities.

While the system is in operation during production, sensors enable engineers to stream data from the seabed to the operations center. This data consists of measurements from flow meters, temperature sensors, pressure transducers and sand monitors.

Once the data is captured from the sensors, the data must be curated so it can be analyzed to gain engineering insight. The scale of this task is typically underestimated when building the digital twin.

The data can be used for informing operating decisions once it is in an accessible format for analysis. These decisions can be for controlling the production rate or the system itself, to help understand or plan maintenance, or improve the efficiency of a system.

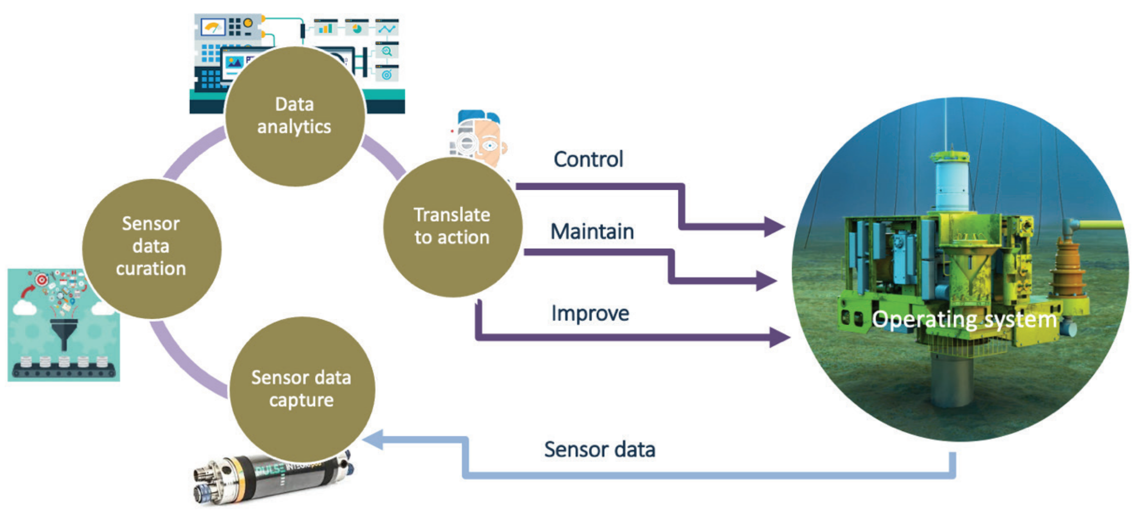

Figure 1. The operational digital twin.

Lack of data

There are many situations where required data may be unavailable. For example, if temperatures, pressures or erosion rates are needed at a location where no sensors are positioned. Additionally, sensors cannot measure future events – even minor unexpected operating conditions can impact a system's efficiency or maintenance requirements, while extreme events significantly impact the integrity or operating life of the system. It is impossible to understand every potential scenario during design.

So, how can we predict future system behavior or evaluate a system's capacity for operating safely beyond design conditions if all we have is data from the past. Similarly, how do we translate data from sensors, which may be in the form of raw data such as sand flow rates, to the damage caused by mechanisms like erosion?

How do we extend maintenance schedules or the operating life of a system, when we do not have experience or data to confidently predict it will continue to operate safely and efficiently?

We need data beyond what is supplied by sensors and design and data from situations that cannot be measured. We also need the ability to transform raw data from the field to engineering insight.

This is the key area that is often missing from the typical elements of the digital twin for operations. The solution is in the ability to obtain data by prediction. How do we predict data that we do not already have and that cannot be extrapolated from historical or design information?

Digital twin for operations – the full loop

Siemens Digital Industries Software has a complete comprehensive digital twin of an operating system when a predictive element is included.

The data from the field and the ability to curate and translate it is required to combine it with predictive aspects. Once we have a full understanding of the data, we can make an engineering judgment or decision.

This analysis can be made by humans and/or machine learning algorithms to translate the data into insights for supporting confident decision-making for control maintenance or system improvement.

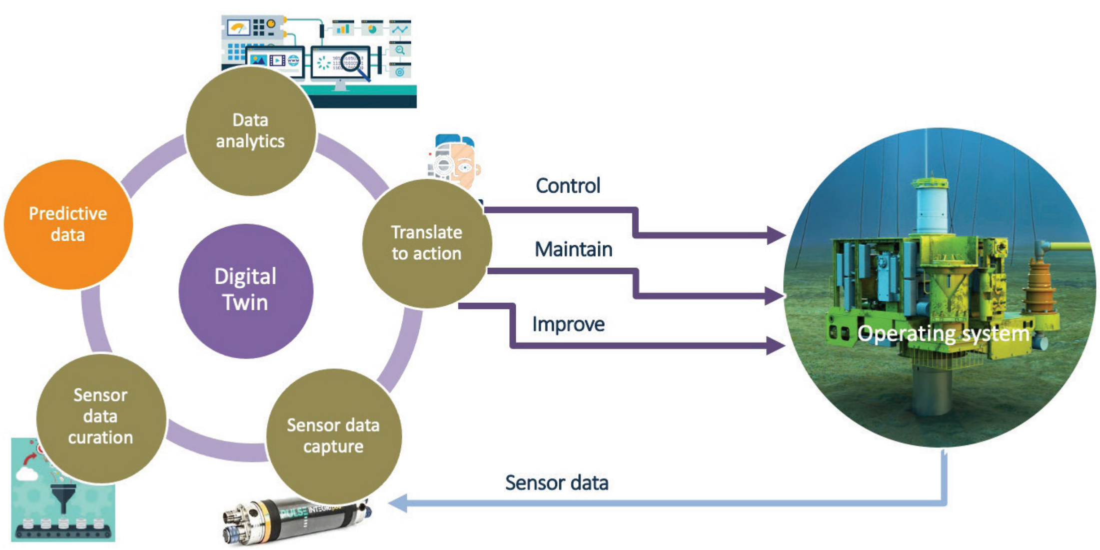

Figure 2. The complete comprehensive digital twin of an operating system.

Predictive data and simulation

The question becomes: What do we mean by predictive data and how do we get it?

Predictive engineering analytics is the application of multi-disciplinary engineering simulation with intelligent reporting and data analytics. Intelligent reporting and data analytics refer to how data is used and processed. What is the role of multi-disciplinary engineering simulation?

Today, simulation is viewed as the application of science-based models to predict real-world behaviors of equipment or complete systems. Examples might be flow simulation based on the Navier-Stokes equation, structural simulations solving the stress or deformation of a system under load or electromagnetic behaviors and phenomena governed by the Maxwell equations. Rather than relying on data analytics from field measurements, it is essential to incorporate science-based approaches.

What can simulation enable us to predict?
We can simulate any real-world physical behavior – such as fluid mechanics, heat transfer, electrical behavior, acoustics, vibration, chemical or structural response by using equations and modeling techniques that follow fundamental scientific principles.

The different ways that simulation is used and the different types and methods available, open different avenues for understanding and predicting product or system behavior as part of a digital twin.

Simulation has different levels that provide a varying degree of detail or fidelity to meet the needs of different real-world applications.

Simulation – high-fidelity
Using geometrically accurate representations of a system or component (typically 3D but can also be 2D or axisymmetric) provide the highest fidelity and most detailed insight into system behavior. This can be flow, structural behavior, heat transfer, electrical or electromagnetic behavior, etc.

This level of detail raises the capacity for predicting complex behaviors using the fundamental governing equations of the physics or science we are seeking to understand. Therefore, tools like computational fluid dynamics (CFD) or finite element analysis (FEA) are examples high-fidelity simulation methods.

To provide this level of detail and insight, high-fidelity simulation tools are typically the most computationally resource-intensive of the levels discussed in this white paper and require the most processing resources. However, they provide the most flexible and comprehensive approaches to solving engineering problems. For example, high-fidelity simulation is used to build reduced order models (ROMs) to provide real-time data.

Simulation – system level
System simulation is an approach that uses a reduced level of geometric detail compared to high-fidelity. System simulations typically employ 1 or 2D representations of a system. They often use the fundamental scientific laws and equations of real-world behavior, but with lower geometric resolution and less detail. This approach requires less computational resources and less time to render the simulation solution. Therefore, it is used for larger, system-level predictions.

Figure 3 presents an example of a subsea production system, with a subsea jumper connecting a production tree to a manifold system. The jumper is shown in 3D (top right corner) and in a system simulation (bottom left corner).

The system consists of insulated pipe with exposed locations (cold spots) at lifting points and sensors. It is terminated at each end with geometrically (and thermally) complex connection systems.

If we need to predict the temperatures at many different locations in that system, what is the best approach? Is high-fidelity simulation required or will a system simulation suffice?

A high-fidelity CFD simulation will use a 3D geometrical representation, enabling us to predict a detailed picture of what is taking place, but it will take longer than a system model. A system simulation provides a profile of temperature but might not fully resolve areas of highly complex geometry, flow or thermal phenomena.

For example, the detailed CFD simulation shown in the top right of figure 3 shows temperature distributions at different points in the system, whereas the system simulation provides single point data along the system length.

High-fidelity simulation is required to understand the 3D flow and thermal behavior. However, if all we need is 1 or 2D information at points along the system, then we can save time and resources by using system simulation techniques. It comes down to the level of detail needed from the data, the amount of time available and whether the approach can capture the required data.

Simulation – ROMs

ROMs refer to a variety of techniques used to reduce the computational complexity of mathematical models in numerical simulations. Typically, at the lowest level of detail and computational resource, ROMs are not based on fundamental scientific principles. They are usually based on a mathematical description of a system that has been tuned (or trained) to match known real-world behavior in a specific set of bounding or operating criteria.

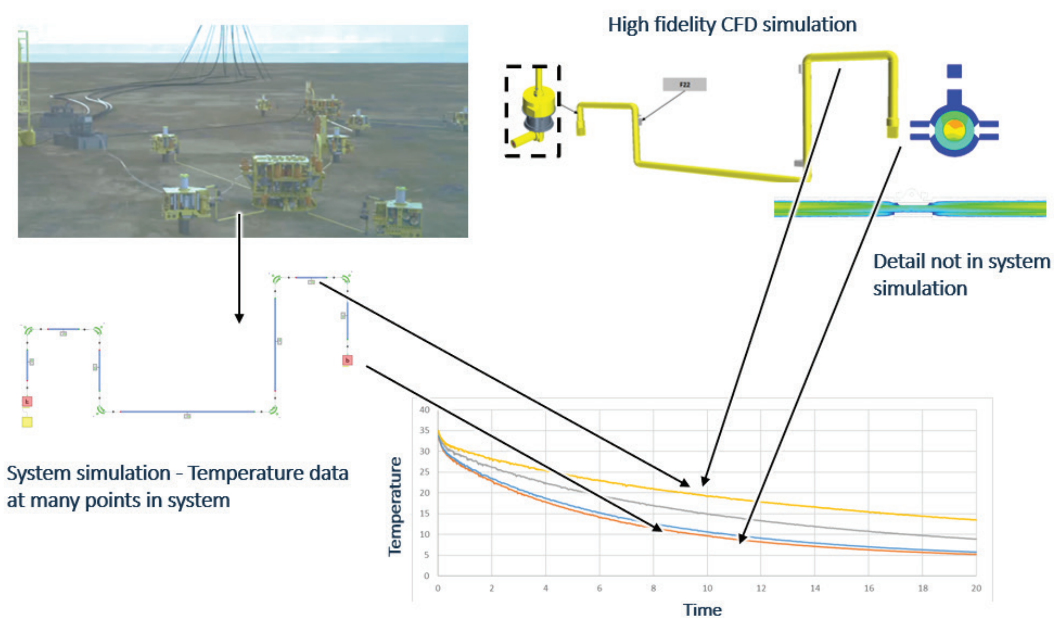

Figure 3. Simulation of a subsea production system.

This tuning and validation are obtained from validated higher fidelity simulations.

Usually, ROMs are low-fidelity approximations, or reductions, of a system, which are used to predict a specific behavior of a system (or its parts) in real time.

ROMs can be created in multiple ways. The simplest ROM is a curve showing how two variables respond to each other to define a behavior at a given location (for example, the changing temperature at a point in a system). As the number of input or output variables increase, we may need to generate response surfaces, where we feed in data on how a system responds and look up that data when it is needed.

Alternatively, we can create simple mathematical (or sometimes science-based) models where, system behavior is described using a set of ordinary differential equations, characterized by the number of parts in a system and the coefficients that need to be trained and validated to predict a specific system response.

ROMs are the least flexible of the predictive approaches discussed but are the quickest and least resource intensive. They rely on the higher fidelity approaches where the data can be used to build the ROM.

How to apply and connect these approaches in the digital twin for operations

The following examples demonstrate how to use each of these simulation techniques and how to bring them together to generate the predictive element of a digital twin for operations and provide valuable insights.

1. Heat exchanger integrity – the predictive element

This first example shows the integrity management of a heat exchanger, which is common to many production and process facilities (figure 4).

In this scenario, steam is passed through a bank of looped tubes. When the steam exits, it transfers its heat to the operating fluid in the surrounding vessel.

The operator advises that temperature sensors are reporting excessively high temperatures in some locations. There is concern this may create thermal gradients, which could generate stresses and fatigue issues that may result in heat exchanger pipe failure. Essentially, there is an integrity risk.

During operation, only temperature can be measured in the system, with measurements limited to temperature sensor locations. However, more insight is needed to understand what is causing the rise in temperatures.

Therefore, insight is needed from localized temperature data. For this, we can use predictive engineering analytics, in the form of simulation, in several ways.

Figure 4. View of an industrial heat exchanger.

First, we can apply high-fidelity computational fluid dynamics to predict flow distributions and/or detailed temperature distributions and heat transfer, to get a complete picture of the system behavior. This shows there is an issue with flow distribution in entering the heat exchanger tube bundles and it is causing temperature gradients.

This temperature data can be used in an FEA to assess the operating life of the system. This would provide the stress history and enable us to predict the impact the stress has on the equipment life.

However, using this approach to assess the life of a system can take a long time due to the complexity of the operating history and life of the equipment. Typically, in these circumstances the high-fidelity approach is too time-consuming to use on its own. Instead, it can be combined with ROMs and trained to rapidly gain the data needed in real time.

Build the ROM

Taking the temperatures from the steam bank (for example, the tubes) can help us understand the flow distribution using fluid dynamics simulation and model the stress distributions for a small set of cases that we have operating data for. We can validate this approach from known operating conditions and measured temperature data. With this data, we can use FEA to correlate operating conditions to stress response and data and use this insight to identify the critical locations for the system's integrity.

If we draw the correlations between the operating conditions and the temperatures at our sensor locations with the stress predicted at the identified critical locations in the system, we can generate an ROM we can train to match the system behavior.

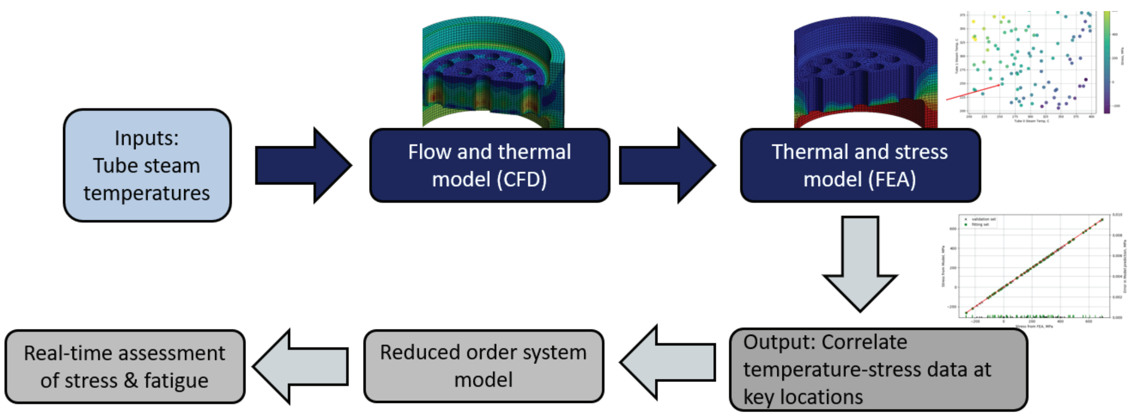

Figure 5. Building a process for heat exchange integrity.

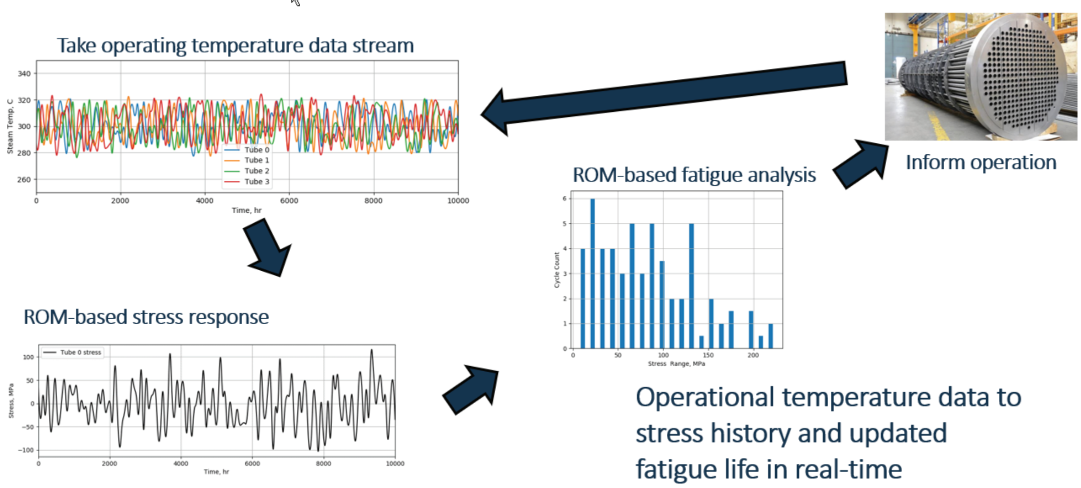

Figure 6. Application of a ROM.

Application of the ROM in operations

In operations, this works by taking the sensor temperature time history data and running it through the ROM. The ROM generates the stress response time history, an updated fatigue life and a remaining life. These can be used to inform operations.

This way, the operational temperature data that be used to create a summary of the structural integrity of the system in real time. This process is demonstrated in figure 6.

The ROM can be used by engineers in operating roles. Engineers, or an algorithm, can explore and plan how to operate the heat exchanger in the future, based on operating requirements, and maintenance schedules.

2. Flow assurance digital twin – the predictive element

This second example is related to subsea production and a major production assurance challenge in the form of hydrate avoidance and risk management.

Subsea production - thermal management

In many subsea production systems, there is a hydrate risk relating the compositions and mix of fluids produced, the operating temperatures and pressures and the system configuration and design. Thermal management is a key aspect of any subsea production flow assurance, whether this is driven by hydrate risk management or to maintain the required operating conditions between the reservoir and production facility. Accordingly, understanding thermal performance of such systems – whether reliant on passive or active insulation, if uninsulated – is critical to successful and reliable production operations.

CFD is a high-fidelity approach commonly used to aid design and validate the thermal performance a subsea system. A CFD-based approach has been proven to reduce time and costs of physical testing programs, which typically cannot replicate real operating fluids and conditions. However, the complex and resource-intensive nature of this high-fidelity simulation approach is not conducive to delivering real-time insight during operations.

In the example of system simulation and the subsea jumper, it is a pipe connecting a production tree, which is used to contract flow and access to a subsea well, and a manifold system, which connects multiple wells.

This highly three-dimensional system is insulated to support thermal performance, but with multiple cold spots and complexities such as the lifting points, temperate sensors, sand detectors and connection systems at each end. CFD is often used to confirm the system is designed to offer optimal thermal performance, but what about during operation?

Operating digital twin 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 significantly vary from design conditions. So, how long do we have between a halt in production before action must be taken to manage hydrate formation risk? Is there more time to make critical decisions than design conditions suggest? Or is there less time?

Typically, when any engineering facility is operational, data is needed in real time and must be available in a manner that can be used to enable engineering decisions. As the heat exchanger example showed, temperatures alone cannot expose integrity of a system. We must convert limited temperature sensor readings to a full temperature field and use this to predict the stress history before we can predict the remaining life of the system. In this example, the predictive digital twin was able to deliver the insight.

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

Using system simulation enables us to build a model of the subsea jumper that represents the high-fidelity model, just in lower fidelity (figure 7).

The advantage of the system simulation approach is that we still make use of fundamental scientific principles in solving the physics of the system like in a high-fidelity approach, but at lower resolution.

This enables us to predict temperatures in the system and across a wider range of scenarios than what is possible with a mathematical ROM.

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 can be used to predict temperatures accurately at all locations in the system to verify a system model. Additionally, the high-fidelity data can be used to tune the system simulation (for example, to account for complex design details or phenomena and their impact on thermal and flow behavior).

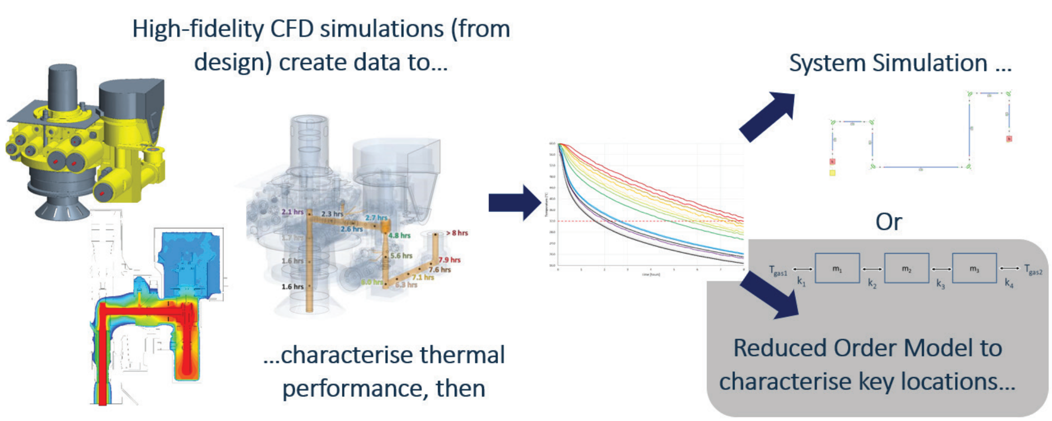

Figure 7. Building a low-fidelity model.

High-fidelity CFD — building the ROM

For some engineering systems we can build a system simulation without needing to train or tune it using higher fidelity approaches. This depends on what is needed from the data obtained and the system complexity. For geometrically or operationally complex engineering systems, we may need to train the system simulation to obtain accurate data.

In this example, four different cases are simulated using the CFD approach. From those detailed simulations, we can identify where the key hydrate risks are and gather detailed temperature data of how the whole system is behaving during production and following a shutdown.

Then, the CFD data is used to build the system simulation. The first of the four CFD cases enable us to train the system simulation. In this case, it is used to tune local heat transfer coefficients and thermal characteristics where complex geometrical features exist in the system or insulation design. With this training data, the other three cases validate the system simulation to verify it will be accurate across all conditions.

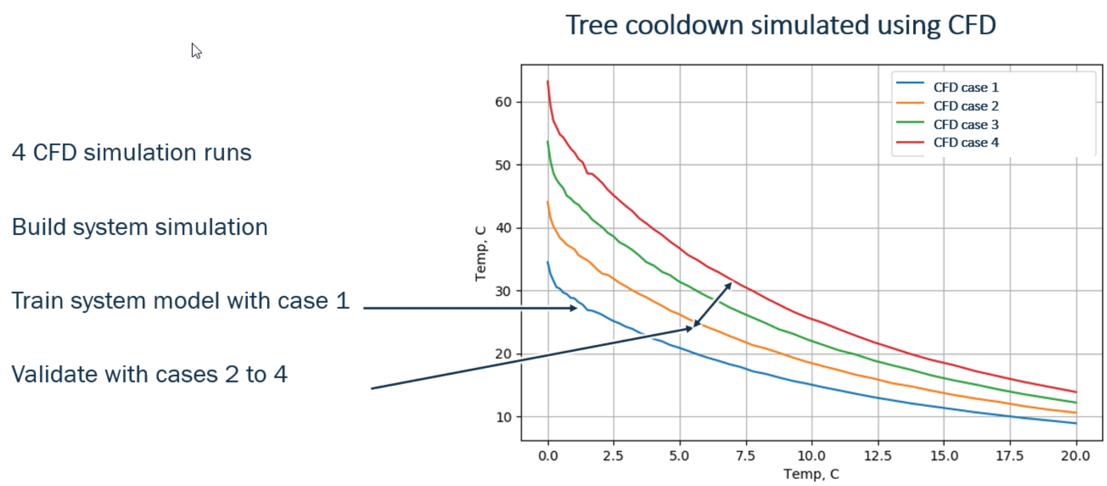

Figure 8. Validation of the system simulation.

Calibrate and train using case 1

Figure 9 shows the CFD cool down data and the prediction using the system simulation at one location where a geometrical feature exists. The left-hand chart displays some difference between the two temperature-time plots. However, by tuning the local heat transfer coefficients and thermal properties, the model can be tuned to demonstrate how the CFD and system simulation data fall on top of each other to provide the benchmark case 1.

System simulation validation using cases 2-4

When that same tuned system simulation is applied to the three remaining cases, there is an excellent correlation, which validates the model (figure 10). Figure 10 presents temperatures at a single location for cases 2 to 4. In each case, the brighter colored line is the system simulation and the darker line is CFD data. There is now an alignment across all locations between CFD and system simulation data.

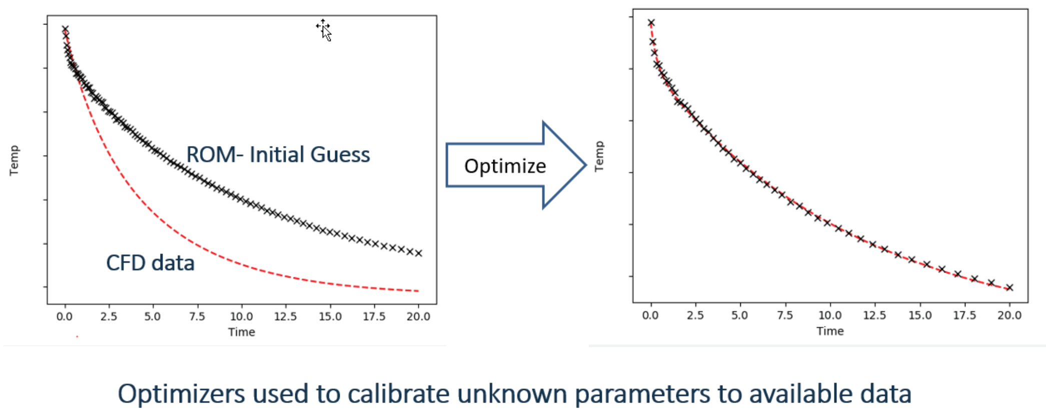

Figure 9. Calibrating unknown parameters.

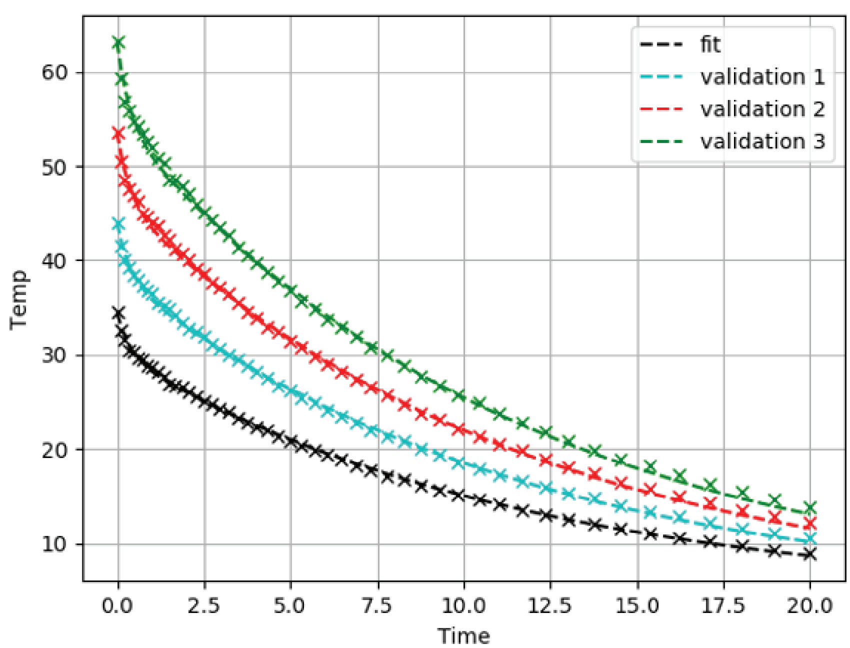

Figure 10. Further validation of the system simulation.

This method enables us to capture the transient thermal response of the complete subsea jumper, which provides a real-time prediction of the risk of hydrate formation.

Here, a high-fidelity simulation was used to create a real-time system simulation capable of informing hydrate formation risk. This can be easily embedded in the digital twin for operations, which enables operators to access a hydrate avoidance strategy that lives alongside the changing operating conditions, providing confidence in critical flow assurance decisions.

Conclusion

The comprehensive digital twin offers a major step-change in how systems can be operated and maintained by delivering real-time insight into efficiency, integrity and reliability. In addition, a digital twin that can predict performance and understand historical performance, delivers the opportunity for engineers to better understand and manage future operational scenarios.

Like any real-world engineering product or system, the digital twin has a lifecycle. Data is generated from initial ideas about a concept and its feasibility and the detailed design, manufacturing and operation stages. If we generate data, we should capture it and use it to inform the next phase of the lifecycle. This white paper showed how simulation data gathered in design can be used to deliver value in a digital twin for operation.

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

Operators, who will put equipment through 25 years' worth of operation must work with the equipment providers, who have the detailed technical and design knowledge of the products, and the technology developers, who have the tools and toolsets to create digital twins and the knowledge of how to embed these in an operation.

Although this white paper has explained a small number of applications, this concept can be applied in many different aspects of operational engineering from integrity management to production efficiency, environmental performance improvements and safety and risk management.

The different types of simulation, from high-fidelity to system simulation and ROMs, each have specific benefits and provide value depending on the situation or scenario considered. As demonstrated here, the greatest value is gained by using a combination of predictive techniques. The most appropriate technique depends on where you are in the lifecycle and the data you need.

Although predictive engineering analytics provides data and insight, it needs to be coupled with field data to gain the full value of the digital twin.

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