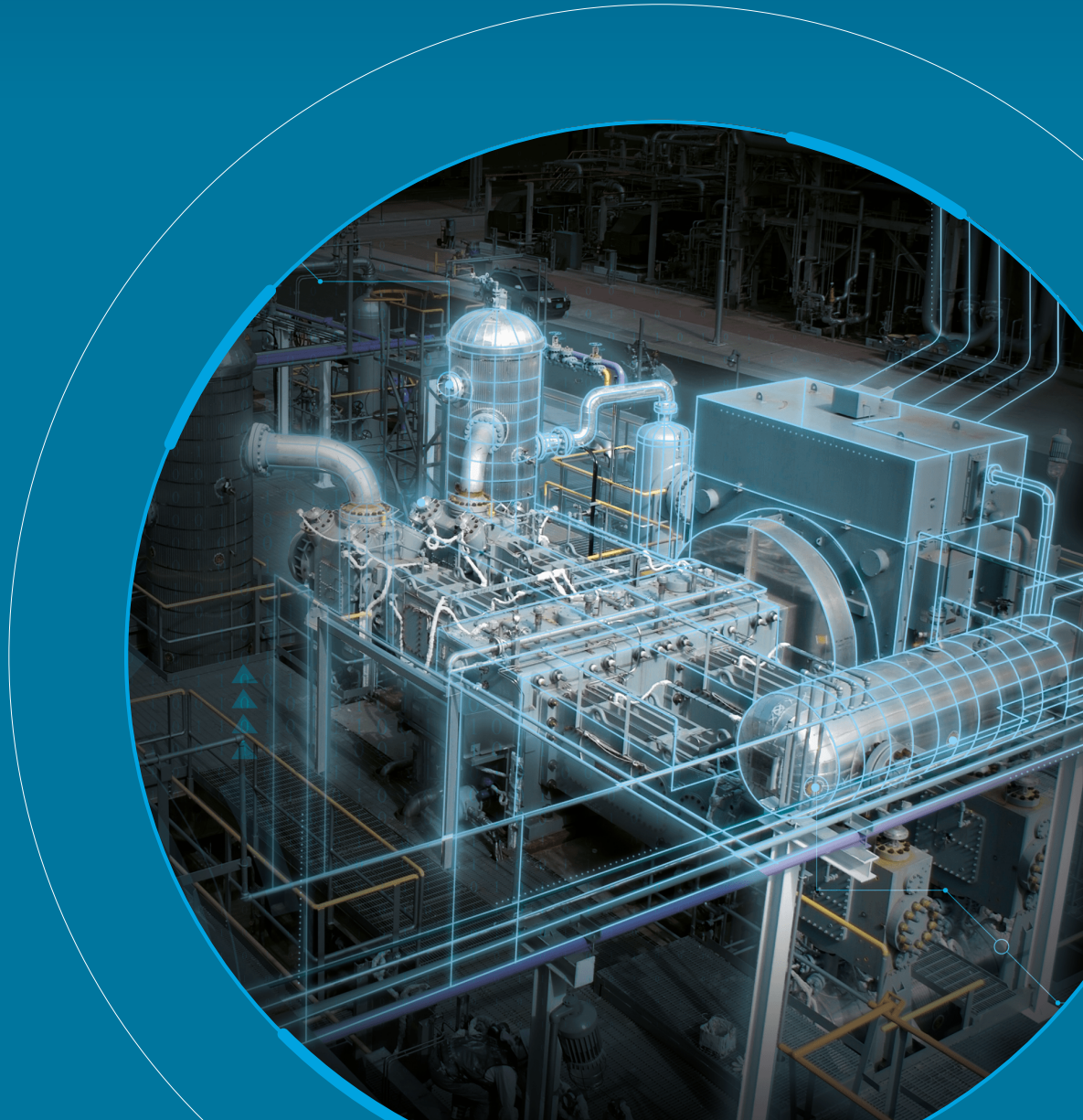


White paper

Predictive analytics using Digital Twins



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Digital Twins in the oil & gas industry

In a complex environment where safety and availability are paramount, predictive analytics drives downtime reduction in the oil & gas industry. Digital Twin driven solutions require a dedicated solution strategy – one that ensures business value creation and guarantees long-term success.

Predictive analytics can provide significant benefits in reducing scheduled and unscheduled downtime and reducing overall equipment operating costs.

Often this links to the concept of Digital Twins – That is, the creation of a dynamic virtual representation of a physical object or system across its lifecycle, using real-time data to enable understanding, learning and reasoning [1].

Application of Digital Twins in complex environments, those found in the petrochemical and oil & gas industries require a well-chosen Digital Twin strategy to optimize business value creation and sustain mid to long-term success.

In his article “**Why Your Digital Twin Approach Is Not Built to Last and What to Do About It Now**”, Jason Kasper [2] outlines some important considerations that address the applicability of Digital Twin strategies in process industry environments. Kasper highlights a foundational concept for the success of Digital Twins in complex environments as follows:

“When you look at an asset in isolation, which is the definition of a pilot project, you will likely see some good results. However, the algorithms are based on one individual asset and its related sensor data. The problem is when you try to scale hundreds or thousands of similar assets. The predictions you created are specific to the asset in the original pilot project.”

Without explicitly addressing the context, Kasper takes the perspective of applying a data-driven machine-learning approach to predictive analytics in the context of a larger group of similar but not identical assets, as commonly found in the process industry.

A key element in understanding the possible applicability of predictive analytics is the relation between homogeneous versus heterogeneous assets and model-driven versus data-driven approaches.

Homogeneous assets are assets which are 100% identical. For example, a large, series-produced type of water pumps operating in virtually identical conditions. Heterogeneous assets, on the contrary, are assets which are similar in nature and principles, but are significantly different in geometry and application – therefore not identical.

Many engineered-to-order rotating equipment assets fall into the latter category. The basic equipment principles are identical (e.g. reciprocating compressors, screw compressors, diaphragm compressors), but every asset is geometrically different, and the operational process environment is also unique.

Further to this, critical assets in process industry applications are relatively reliable. Whilst the variety of possible failure modes is large, even years of historical data will only include a limited number of failures. This reduces any 'big data' package to a small data package, only covering a limited selection of all possible failure modes.

Data-driven and model-driven analytics

The specific features of rotating equipment in the process industry make data-driven predictive analytics, using machine-learning algorithms, less effective in these heterogeneous asset groups. Trained, self-learning algorithms, detect failure modes based upon qualified or unqualified historic data.

This suits homogeneous asset groups better. Generally, these assets have a larger quantity of, and more diverse training data available. Thus increasing the strength and applicability of the algorithms and improving the quality of results across a wider group of assets.

The predictive quality of machine-learning algorithms for heterogeneous asset groups suffer from the quantity and quality of available training data datasets. These training datasets are leaner in size and quality: not covering a wide range of failure modes, and each training dataset only limitedly applicable to other assets.

This leads to the described situation where self-learning algorithms are able to provide good results on a single heterogeneous asset, but cannot scale to enterprise level. Each new heterogeneous asset requires a substantial amount of re-qualification and re-training of the algorithm. Overall the results are highly dependent on the available historical data of that particular asset.

A model-driven approach to predictive analytics is able to overcome this deficit [3].

Model-driven predictive analytics apply physics and simulation-based models to analyze asset data and exhibit predictive capabilities by recognizing and qualifying asset behaviour in relation to failure modes and operating characteristics.

This implies that there cannot be a general model-driven algorithm applicable to all asset types, as the model development requires deep domain knowledge to provide the asset-specific predictive capabilities.

This makes this approach suitable to asset populations which are diverse but similar in nature, or where qualified historical data is not sufficiently available in order to train capable self-learning algorithms.

Model-driven predictive analytics which is scalable at an enterprise level is asset-agnostic at the core. This means that the underlying physics and simulation models do not include specific equipment data, such as geometry or other design considerations. This data is being provided and validated in real-time by a second-tier model layer.

This effectively provides model-based analytics with self-learning capabilities and enables rapid scalability across entire asset populations. It also bridges the gap between as-built or factory data as the model-driven Digital Twin becomes responsive to real-time data.

This ensures that any changes in design, maintenance actions, and field modifications, or changes in process parameters reflect and become embedded in the Digital Twin – rather than invalidate the conclusions and therefore support sustained value of the Digital Twin in operational environments.



Hybrid Digital Twins

Data-driven and model-driven analytics are not strictly separate approaches. The characteristics and strengths of both approaches can be combined by constructing interactions between model-driven and data-driven solutions.

In this way, data-driven analytics can support early identification of deviating asset performance patterns using unsupervised machine learning.

Leveraging the scalability of data-driven analytics enables cross-asset pattern recognition building on the augmented data output provided by the model-driven Digital Twin, and thus, further enhances the predictive capabilities of the resulting hybrid Digital Twin as a whole.



Evolving architectures

Further to the addressed Digital Twin specific characteristics required for scalable and long-term success in complex environments, it is worth emphasizing the architectural considerations which support a future-proof Digital Twin strategy.

Citing John Gugel from his article “Executive Viewpoint: Introducing the refinery of the future” [4], the future refinery or petrochemical plant will be a digitally connected facility, equipped with cloud-based connected plant services, supporting operational improvements and providing insights and guidance to plant operators. This is part of a continued journey through OT (SCADA, RTU etc.) and IT transformation, cooperation, and integration.

A proper Digital Twin application strategy also addresses this future perspective. As OT and IT environments continue to change in response to business needs and technological advances, selecting a future-proof software and hardware solution architecture is key in ensuring continued and maximized benefits.

One of the primary aspects in maximizing future usability of Digital Twin driven solutions is the openness and scalability of the complete Industrial Internet of Things (IIoT) stack – from data-capturing, communication, storage, processing and analytics, to user interfacing.

Selecting solution elements which fit into an open architecture allows continual alignment with evolving IT and OT environments.

Thus giving the ability to interface different functional elements of the digital solution in line with the current and future business needs (Figure 1).

IT requirements of the solutions environment might change over time as scale and environment evolve. Accounting for these future requirements makes selecting an architecture for initial deployments complex as it introduces risks with regard to long-term useability. This risk can be mitigated by using an open solution architecture.

An open architecture allows transitioning from off-premise cloud-hosted to on-premise or on-premise integrated architectures, directly interfacing or integrating with plantwide IT or OT systems, providing a future-proof foundation for IIoT applications.

This also provides the ability to deploy Proof-of-Concept or small-scale solutions at a rapid pace without significant infrastructural investments, whilst still having the flexibility to modify integrations and interfaces as business or scale requirements change.

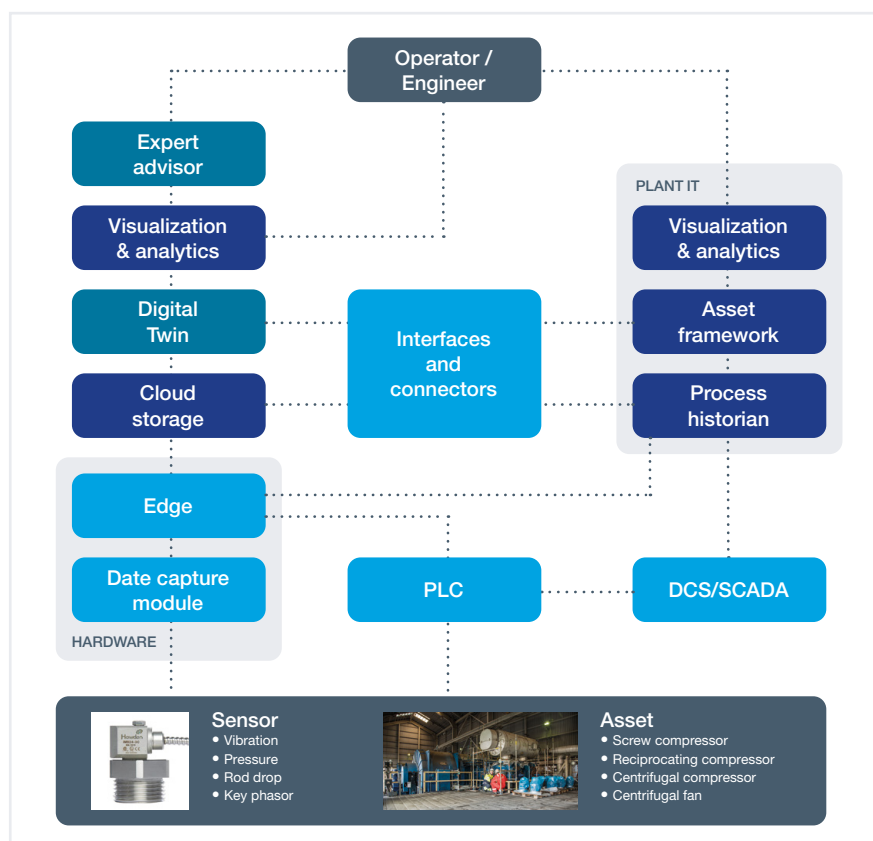


Figure 1: Predictive analytics IIoT stack for process applications.

Conclusion

Defining a Digital Twin strategy which is closely aligned with the operational environment and asset types under consideration is instrumental to support business value creation. Depending on the asset type, the appropriate Digital Twin solution may be model-driven, data-driven, or a combination of both.

The solution architecture which encompasses the Digital Twin should be designed to allow future integrations and interfacing across the IIoT stack to ensure long-term results.

Find out more about the impact of digitization in the manufacturing space and how to drive business value with Digital Twins **by downloading our impact of digitization whitepaper.**



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