Digital Maturity in Alumina Refining

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Abstract

The rapid advancement of digital technologies and methods promises to have significant impact on the alumina and processing industry. Modern tools in machine learning, internet of things (IoT), cloud computing and real-time mathematical optimization are becoming more accessible and commonplace. These tools are being used to transform the refinery design process, improve productivity of operations, reduce maintenance cost, and offer the opportunity to redefine business processes and business models. Having knowledge of these rapidly developing digital technologies combined with deep domain expertise is key to unlocking value and delivering on the business case. This paper introduces the concept of digital maturity and provides a structured approach for considering digital transformation of complex processing plants. Moving through stages of digital maturity, process data is first used to provide visibility of the operation and generate process insights. Insights provide a ground truth to allow the development of predictive models. Predictive models then allow scenario evaluation and optimization to assist in making the right decisions from a facility to refinery-wide level. This may be by way of determining process targets, optimizing maintenance activities, or other means. An example of this approach to digital maturity is presented for the digestion facility of an alumina refinery. Here, modern software systems provide an interactive and intuitive means to assess current plant performance and provide real-time process insights and diagnostics of operational issues. Predictive asset reliability information is also generated to assist in maintenance planning by highlighting at-risk equipment and providing estimates of residual equipment life.

Keywords: asset reliability, predictive maintenance, digestion, digital transformation, digital twin.

1. Introduction

This paper demonstrates how modern digital technologies and methods may be applied to help tackle significant or poorly understood challenges in the refinery operations setting. One approach, as currently being undertaken by Hatch, is presented for such a challenge in the pressure letdown area of an alumina Digestion facility. Here, certain operating modes may lead to widespread and aggressive rates of erosive wear throughout the asset, representing a significant impact to operating costs. Further, under some operating modes erosive wear may be so severe that piping components can fail unexpectedly resulting in significant safety and environmental incidents through release of high pressure caustic slurry.

Supporting the above objective, the concept of digital maturity is introduced to provide a structured approach for the application of digital tools. Focus is firstly placed on providing a framework for consolidating all relevant information and data on an asset-centric basis. Secondly, live digital tools are progressively applied to support operations and maintenance decision making. Central to achieving this aim, complex multi-phase hydraulic models are deployed to provide live insights into current operation as well as predictive information for future asset condition, and to enable simulation across a variety of process and mechanical variables.

2. Digital Maturity

The concept of digital maturity is complex, can take on many forms, and represents a continually evolving journey [1]. The digital maturity of an organization or operation could be measured by its digital strategy or vision, by its governance or change management practices, or even by its culture. A challenge facing many organizations is the internal collection, management and use of data and information; particularly information regarding the design, operation, maintenance, planning and performance of their key assets. Because of this, it is useful to think of digital maturity in terms of the management of data and information.

Digital maturity is often a difficult balance between functionality, complexity and value. ‘Big bang’ approaches to highly integrated, smart and automated systems can be costly and face significant change management challenges. Overcoming legacy aspects associated with established brownfield systems also make this approach impractical. A more desirable approach is one which gains incremental functionality, complexity and most importantly value. Focus is placed on demonstrating value at each stage of digital maturity by realizing specific and measurable business cases.

Figure 1 shows one such trajectory through various levels of digital maturity. It shows how an operation might progress from being reactive in nature, through to fully understanding the present, and ultimately being able to predict and avoid undesirable events.

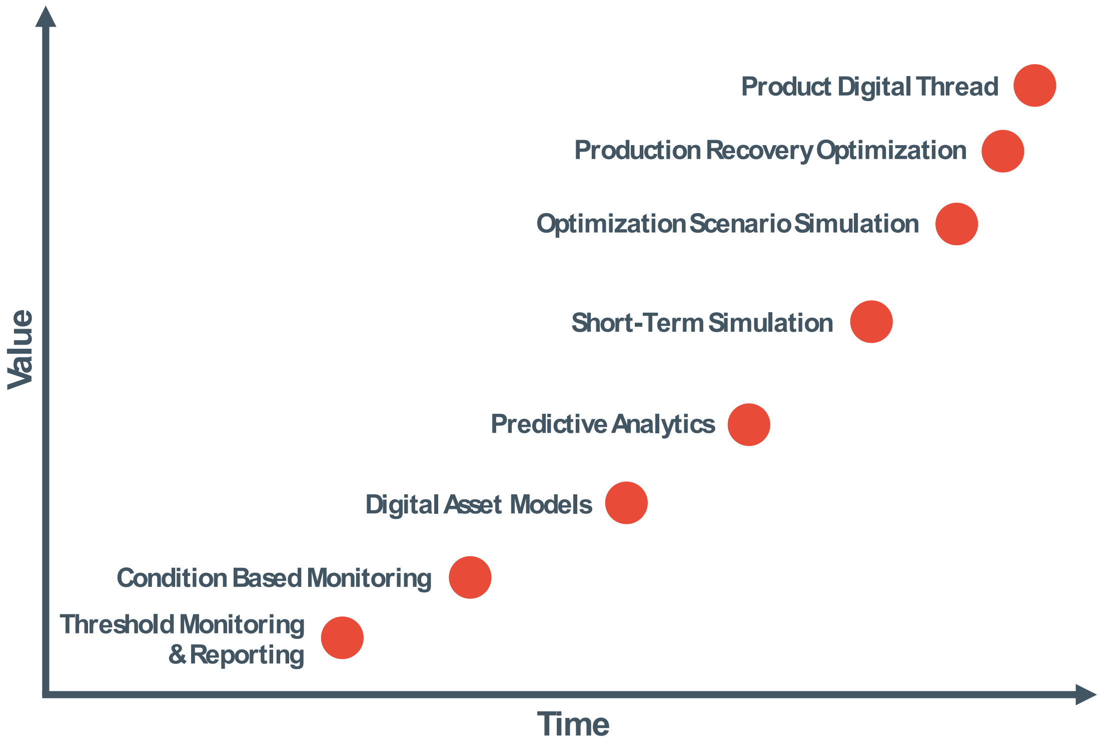

Figure 1. Digital maturity curve.

Moving up the steps presented in Figure 1, we progressively become better at contextualizing, communicating and drawing value from data and information. Further, each step draws on the value and insight generated from the steps below it. This ultimately builds our capability for better realistic and long-term planning through the elimination of uncertainty.

This paper demonstrates how the above may be progressively applied, and the approach Hatch is taking to tackle a specific refinery challenge to ultimately realize its associated safety and environmental benefit, and its business case.

3. Application to Alumina Digestion Facility

The concept of digital maturity has been applied to tackle a key challenge in the pressure letdown area of an alumina Digestion facility. Here, the facility is subject to highly erosive flow conditions emanating from elevated velocities of flashing/boiling abrasive slurry. Consequently, slurry piping and fittings within these facilities, including valves, piping spools, control elements and other wear consumables, are subject to continual non-destructive testing (NDT) for wall thickness measurement as well as regular internal inspections and change-outs.

Certain operating modes may lead to widespread and aggressive rates of erosive wear, resulting in the need to frequently remove the equipment from service and replace piping components that are nearing their minimum allowable wall thickness. This obviously presents as an increase in operating costs due to short equipment life, as well as potential lost production if plant shut-downs are required to allow access for maintenance.

Further, under some operating modes erosive wear may be so severe that piping components can fail unexpectedly in a matter of shifts or days, whereas NDT campaigns may only be performed on a monthly or quarterly basis. This results in a significant safety and environmental incident through release of high pressure caustic slurry.

The objective of this paper is to progressively build the capability to monitor and understand piping erosion such that we can take positive action to prevent the above from occurring. Our initial focus will be to fully understand the current asset condition and the links between operating modes and rate of piping component wear. Focus will then shift to providing analytics, where predictive information will be generated to forecast remaining life for each piping component. Finally, aspects of simulation will be included to allow for what-if scenario testing, providing the refinery engineer or operator the ability to determine the best course of action to avoid undesirable events.

An asset-centric focus has been adopted whereby the facility 3D model forms the basis for the tool, in which all relevant information is incorporated (Figure 2). In essence, this tool is a digital twin of the digestion facility – a dynamic software model that provides a centralized and evolving digital repository of data, information, digital models, and analytics.

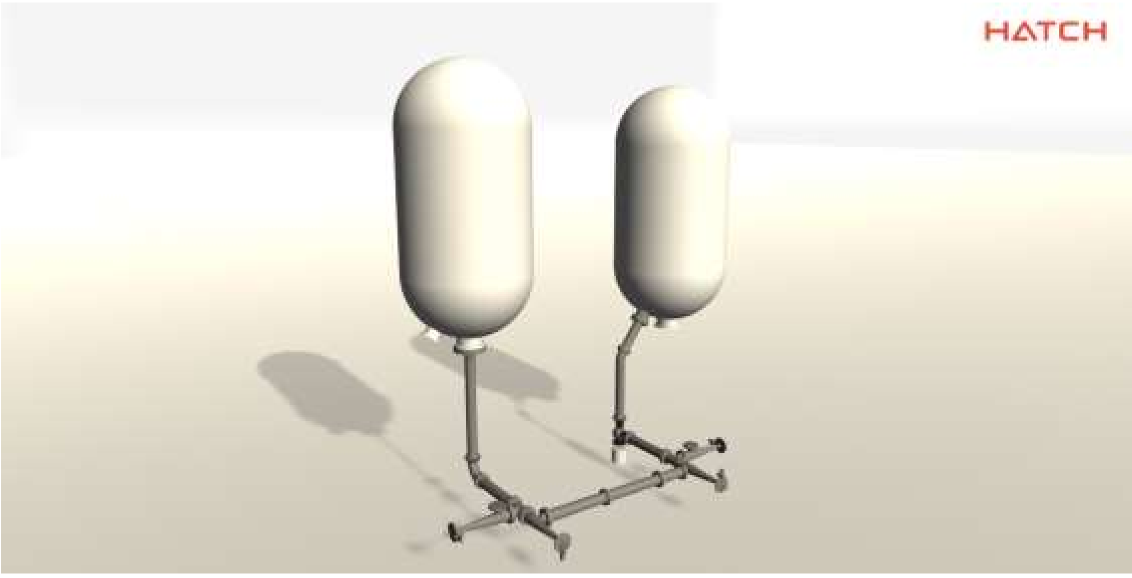

Figure 2. Digital twin basis – 3D model of digestion flash tanks.

The following sections progressively describe the various stages following the Digital Maturity Curve presented in Section 2 and shows how they are applied to meet our objective.

3.1. Threshold Monitoring & Reporting

As our launch-point for moving up the Digital Maturity Curve, this step is focused on ensuring the quality, consolidation and availability of our core process data and plant information. Many different sources and forms of information must be brought together to inform site personnel to allow them to plan, communicate and act in an effective manner. This information is varied, and typically includes process data and threshold targets from the process historian, control system, maintenance data and other sources of less dynamic information such as design calculations and drawings. Information may be distributed across multiple proprietary information management systems (or even archived in hardcopy form) and presents an initial challenge to achieving a consolidated and accessible centralized data source.

This level of digital maturity is common to most operations, albeit to various levels of effort. Site personnel collate and review data and information against targets (thresholds), generate trends, develop plans, and communicate issues and objectives to broader operations teams. Some or all of this process may be automated with spreadsheets or dashboards.

3.1.1 Application

A robust and intuitive means of data and document access is required as a precursor for moving up the Digital Maturity Curve. By using an asset-centric approach information is consolidated and accessible by selecting the equipment or plant component itself, as opposed to a typical menu structure seen in many information management platforms.

Datalinks are established to link in the various repositories of this information, meaning information is brought together from many different dimensions including:

- Live plant data from the process historian
- Live maintenance data such as maintenance schedules and warehouse inventories (spare parts stock levels)
- Maintenance information including maintenance reports, inspection photos and procurement documents

- Design documents, detail/fabrication drawings, calculations, process flow diagrams, P&ID's etc.

Live key information manipulates the 3D model itself, such that the user can rapidly assess the status and performance of the asset. Live plant data is graphically shown in the model where logical, such as visual tank levels or a gauge for control valve position. Other key data is shown numerically and is dynamically colored based on its value and threshold targets.

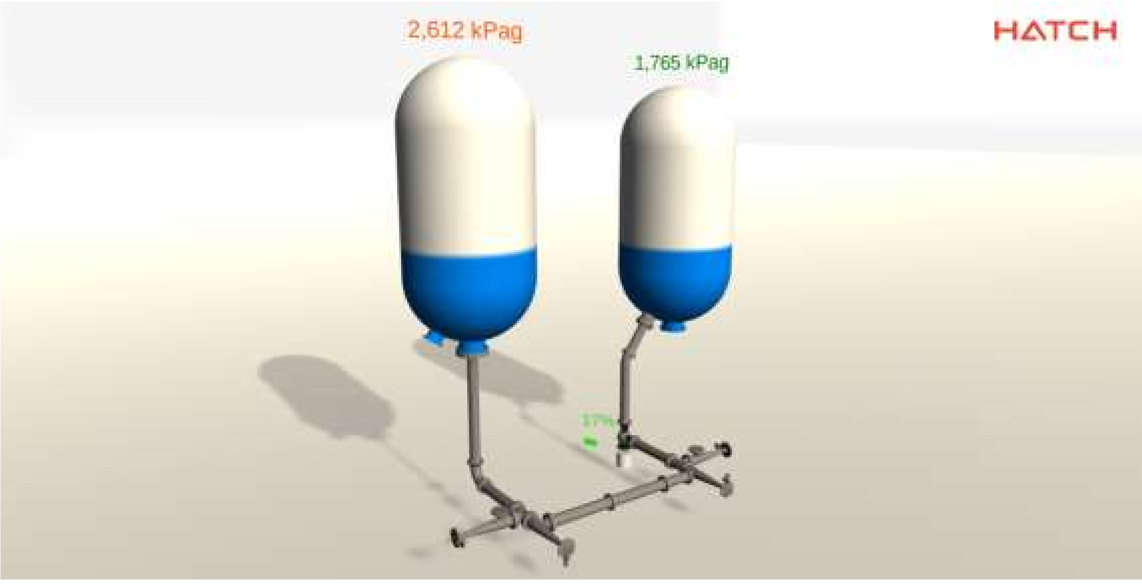

Figure 3. 3D interface with live data model overlays and manipulation.

Selection of each element (tank, valve, piping component etc.) provides access to all relevant information. This is grouped based on the nature of the information (live status, maintenance or design) with direct links to documents regardless of their source repository.

Figure 4. Example of asset-centric information management for an angle isolation valve.

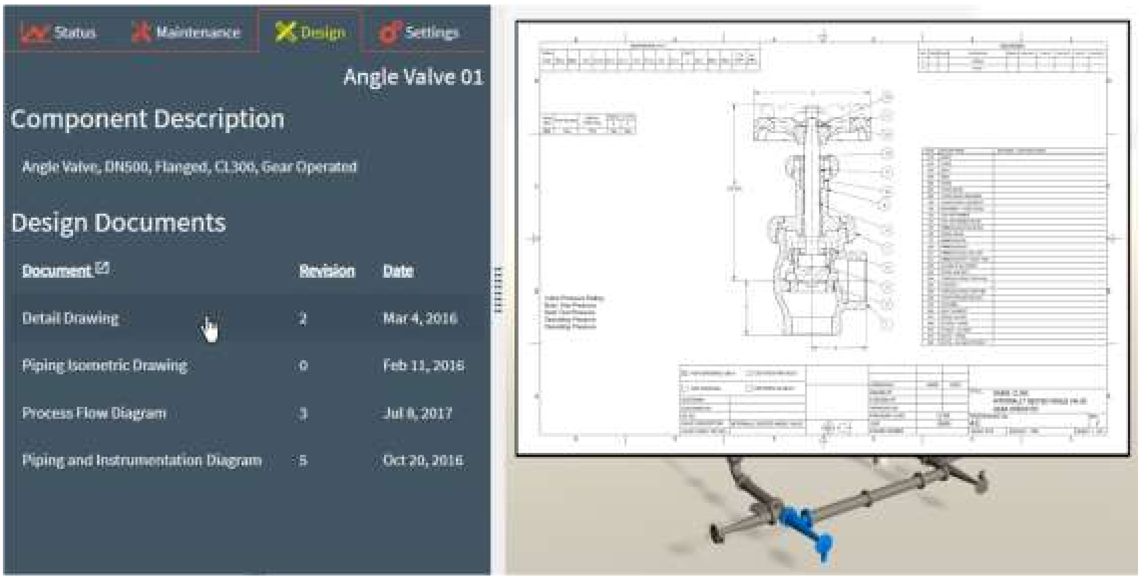

Figure 5. Design information and documents for an angle isolation valve.

3.2. Condition Based Monitoring

Condition Based Monitoring involves tracking the status of an asset over time, and often while in operation. This visibility of actual asset condition can help pre-empt equipment failure and enable better decision-making around when/what maintenance is required (commonly referred to as condition based maintenance). Maintenance activities can be scheduled for when asset performance decreases, or a failure is likely. This has the benefit of optimizing maintenance efforts and minimizing spare parts inventory. Common Condition Based Monitoring examples include:

- Vibration monitoring of pump to track impellor or bearing condition
- Periodic non-destructive wall thickness measurements of vessels & piping to monitor corrosion
- Acoustic monitoring of flanges for leak detection.

Traditionally, Condition Based Monitoring has been performed using live or portable sensors. Challenges include the sensor and installation cost, maintenance requirements for the sensors themselves and the ability to turn generated condition data into reliable and actionable information about the asset condition.

Advanced analytic methods may be employed here to help separate actual condition information from noise. By way of example, consider the condition monitoring of a gearbox installed on an electric drive. Analytics may be employed to filter the noise of an electric current sensor to isolate the signal that indicates overall gearbox condition.

3.2.1 Application

Piping components within the Digestion slurry pressure letdown area are subject to continual NDT for wall thickness measurement. This is often a manual campaign-based effort (e.g. quarterly), where portable radiography or ultrasonic meters are used to measure pipe thickness at multiple points along each piping component. This significant amount of data is often stored in the site information management systems or process historian.

By linking to this data into the digital twin, it may be displayed in the interface (Figure 6) and mapped to its corresponding spool in the 3D model (Figure 7). This provides a 'heat map' style visual system for the effective and quick identification of areas for focus. This heat map may provide various levels of information, including:

- Remaining wall thickness for each assessment location of each piping component
- Residual life of the piping component based on thinnest location
- Rate of change of wall thickness since the last NDT campaign.

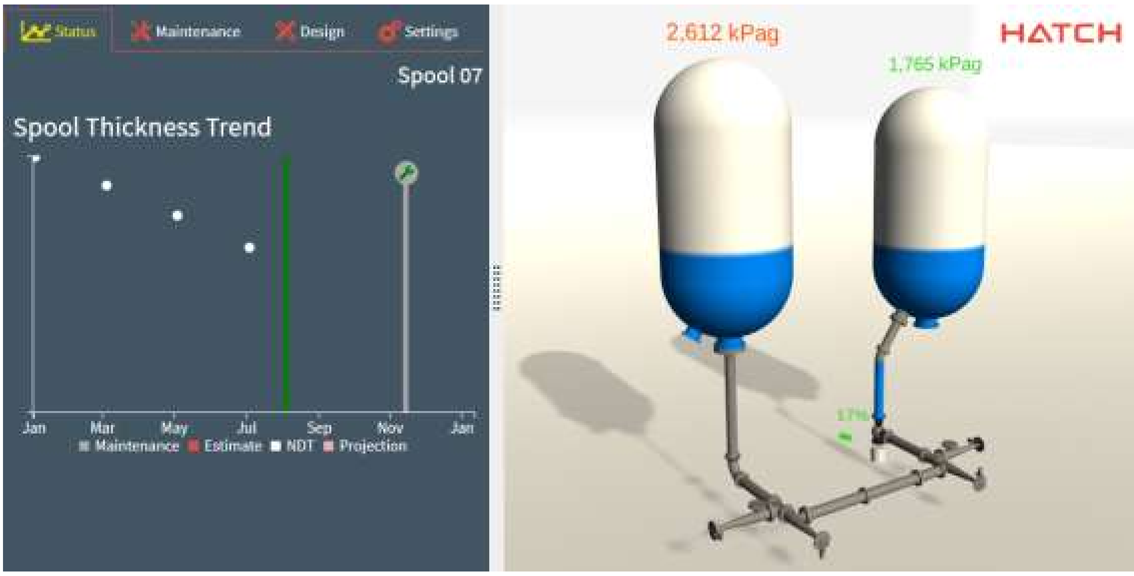

Figure 6. Chart displaying NDT data for selected piping spool.

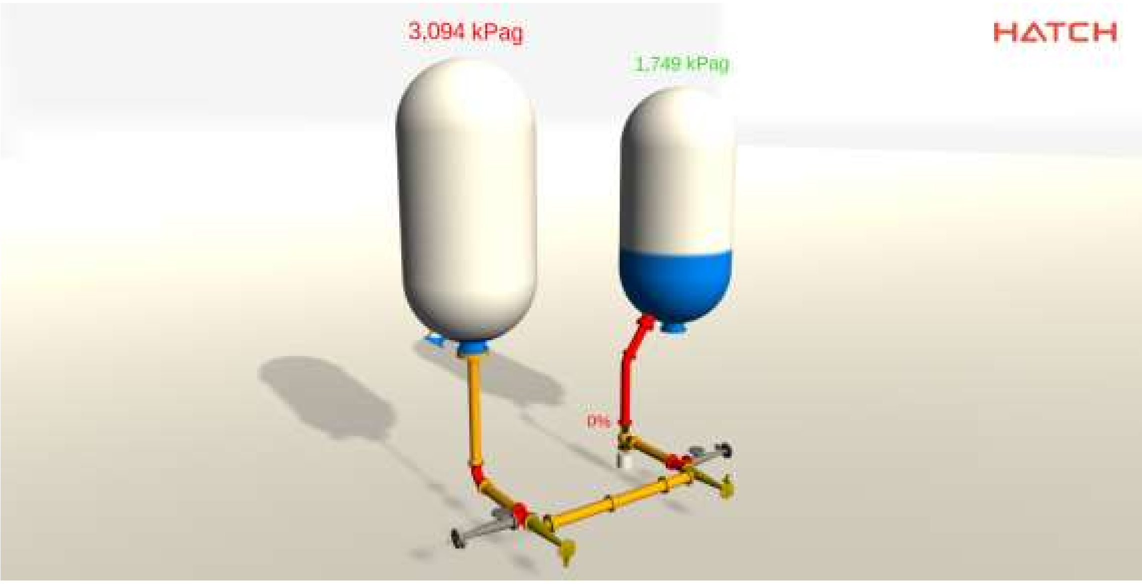

Figure 7. Remaining pipe thickness data overlaid on digital twin.

While this provides a clear visual indication of areas for focus, the intermittent nature of manual pipe thickness measurements means that events of significant piping wear may occur between NDT campaigns. It follows that unexpected piping failures may occur between NDT campaigns resulting in significant safety and environmental incidents.

3.3. Digital Asset Models

The chief role of a digital asset model is to provide context to plant data to help generate insights into asset performance or condition.

As a basic example, consider the operation of a shell & tube heat exchanger. Data may be readily available for each stream entering and leaving the heat exchanger, however the performance and condition of the equipment cannot be easily determined by review of this data alone. Running this data through heat exchanger design calculations allows for the back-calculation of overall heat transfer coefficient, which can be tracked to monitor heater fouling over time. In addition, hydraulic calculations may be deployed to consider the pressure drop across the heat exchanger tube-side in conjunction with tube-side flow and process fluid properties to accurately track tube-side fouling.

The ability to use complex models has increased dramatically in recent years. Large or complex process models, including complex calculations used in the design realm, may now be deployed as live tools. These may be cloud-based, bringing convergence times from minutes to seconds, and enabling real-time analysis.

3.3.1 Application

While there is often awareness of the importance of maintaining the Digestion facility within its design operating window, the exact link between key process variables (e.g. flash tank pressures or digestion feed flow) and slurry piping wear is often not well understood. Complex multi-phase hydraulic models, validated through site trials [2], are deployed in near-live time to provide a direct visual link between Digestion facility operation and multi-phase slurry flow velocities on a piping component-by-component basis.

Using existing instrumentation (flash tank pressures, digestion feed flow etc.) real time mass & energy balances are used as inputs to the multi-phase hydraulic models. These models show the onset for multi-phase flashing flow and the resulting velocity profile as the flashing flow propagates throughout the piping system.

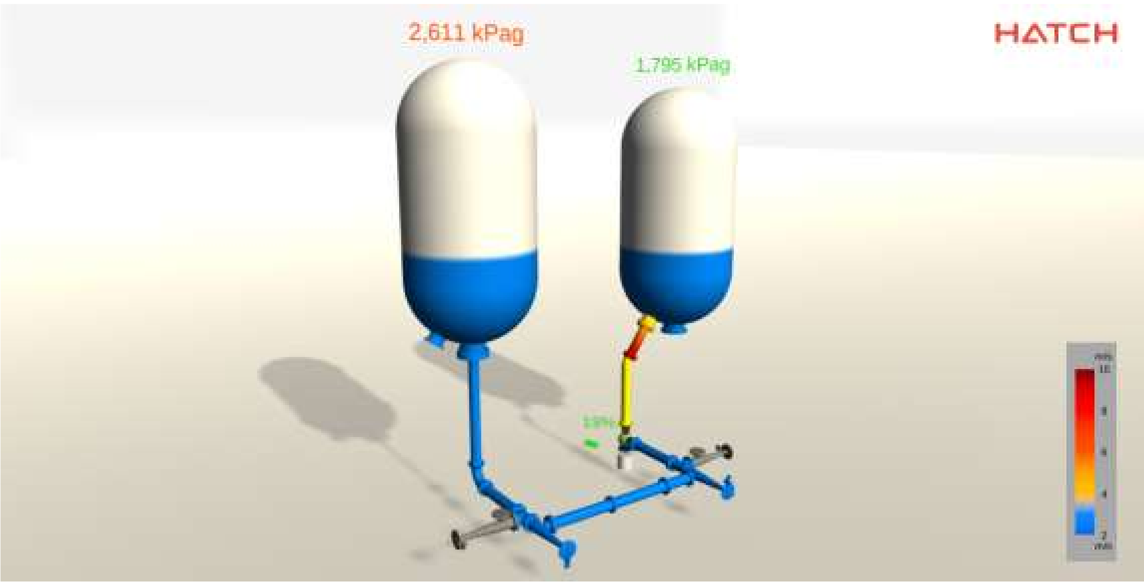

Figure 8. Live multi-phase flow velocity indication for a slurry piping system.

Figure 8 presents this information overlaid on the 3D piping model, with single phase flow represented in blue and multi-phase flow and associated velocities indicated on a yellow-red scale. The presence and extent of flash vapour bypass is also calculated, whereby vapour passes to the downstream flash tank via the slurry underflow piping rather than reporting to the digestion heaters.

This application of a Digital Asset Model utilizes existing plant data to provide real-time process insights that have previously not been available. The plant engineer or operator has a direct visual link between the current process conditions and the resulting impact on asset integrity. If necessary, action may then be taken by adjusting the mode of operation or by managing turnaround or NDT frequencies.

Additionally, to supplement and focus NDT efforts, continual condition-based information is also generated to monitor each piping component between NDT campaigns. Multi-phase flow velocities are used to approximate instantaneous rates of erosive wear, allowing for the live tracking of asset condition and a higher fidelity of asset reliability information.

The link between flow velocity and instantaneous wear rates is initially based on established relationships for slurry erosion on steel piping. As can be expected, empirical testing has found that the coefficients in such relationships are highly dependent on pipe component geometry factors as well as slurry physical properties and may change over time [3]. Advanced data science methods may be employed to automatically fit and adjust this relationship for each piping component and measurement location as new NDT data is generated. Starting with the latest NDT data point, instantaneous wear rates are integrated over time to generate approximates of residual piping component thickness. On receipt of new NDT data, the approximated thickness can be compared against actual thickness, and the appropriate refinement of the erosion coefficients can be made for each piping component.

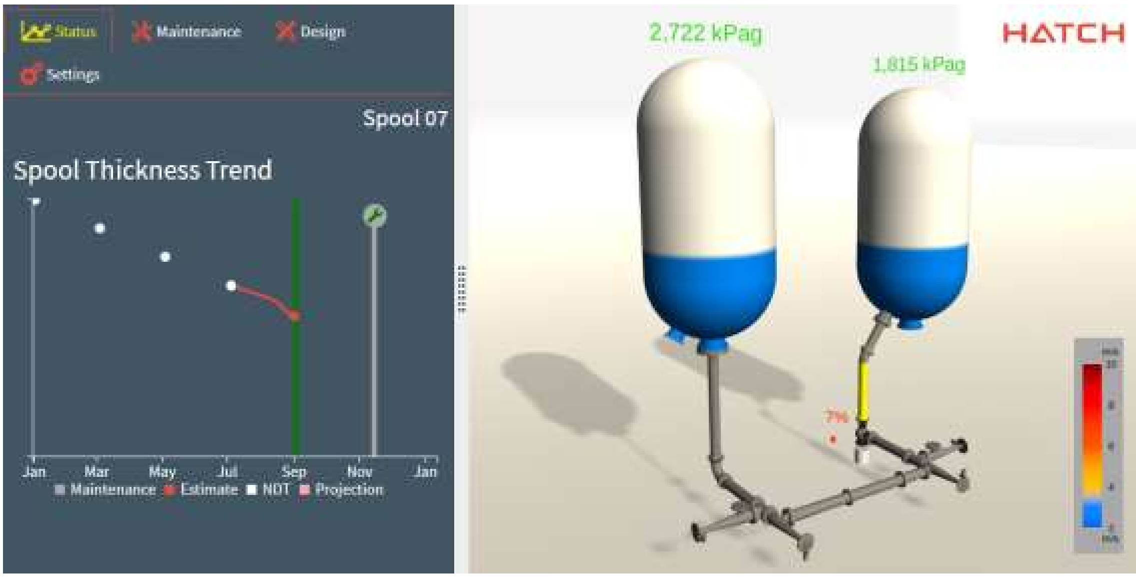

Figure 9. Live approximations of piping spool remaining thickness shown in red.

For installations where reliable flash tank level data is available, the condition of key hydraulic components (restricting orifices, control valves) may be monitored. As an example, Figure 10 shows the calculated control valve position as required to maintain the reported flash tank level. Also shown is the actual field feedback position of the valve. The difference between the two positions highlights a potential issue with the valve, where the current condition of the valve trim (value plug and seat) may be degraded and requiring replacement. This condition information may be tracked over time and used to guide maintenance scheduling and ordering of spare parts.

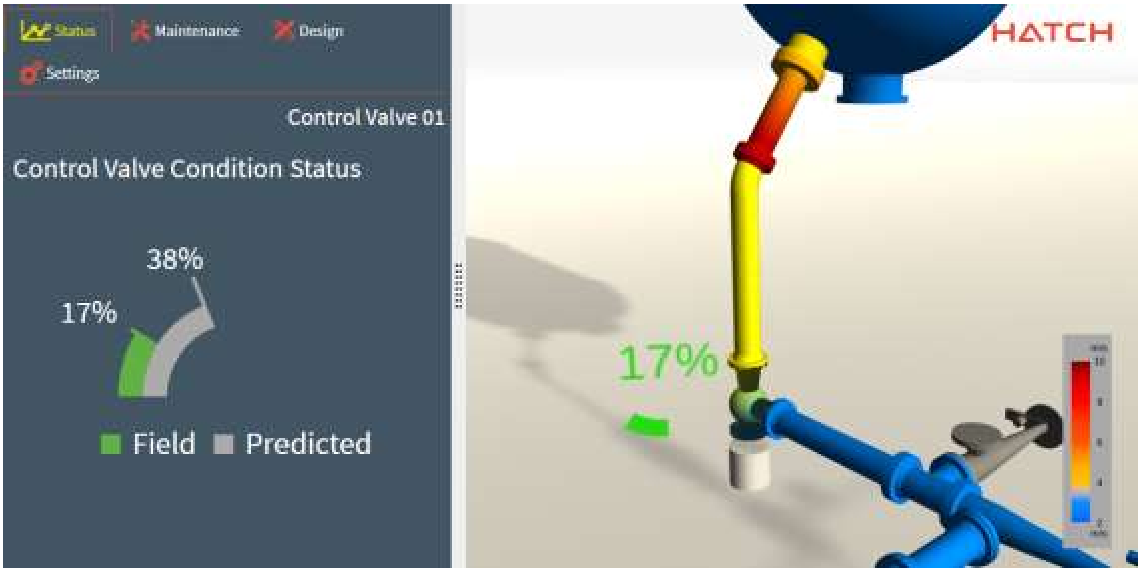

Figure 10. Condition monitoring of control valve, calculated vs feedback position.

3.4. Predictive Analytics

Starting with the clear visibility of what has happened, and a sound understanding of why it happened, Predictive Analytics aims to use this information to predict what will happen. This generates predictive asset reliability and production information to help pre-empt mechanical failures or process disturbances.

Broadly speaking, there are two approaches to help predict the future:

1. Bottom-up generation of predicative information from first principles, whereby the asset performance is tracked against its design/known envelope
2. Data driven/machine learning approach that correlates each mode of operation with the observed outcome or consequence from historical data.

Consider again the heat exchanger example, whereby the heat transfer coefficient (HTC) degrades over time. One may expand this assessment to include additional sources of information to predict the rate of HTC decay. In an alumina Digestion facility, a primary cause of heater degradation is the formation of silica scale on the heat exchanger tube walls. Silica levels in the bauxite feed may be used to predict the rate of heat transfer degradation over time and hence guide the scheduling of heat exchanger cleaning rotations. This link between bauxite silica level and heat exchanger degradation may either be based on chemistry fundamentals or purely based on observed links through the application of a data driven/machine learning approach over a significant dataset.

3.4.1 Application

Building on the approximated wear rates calculated from the established Digital Asset Model, projections of remaining component life may be generated. These projections flag where a piping component is predicted to reach its minimum thickness before the next planned maintenance period, allowing corrective action to be taken. The engineer or operator may elect to change the process conditions or, if required, target further NDT for the piping components at risk. Figure 11 depicts such a situation, where the Predictive Analytics suggests current operating conditions may lead to the selected spool degrading below its minimum thickness before its next maintenance period.

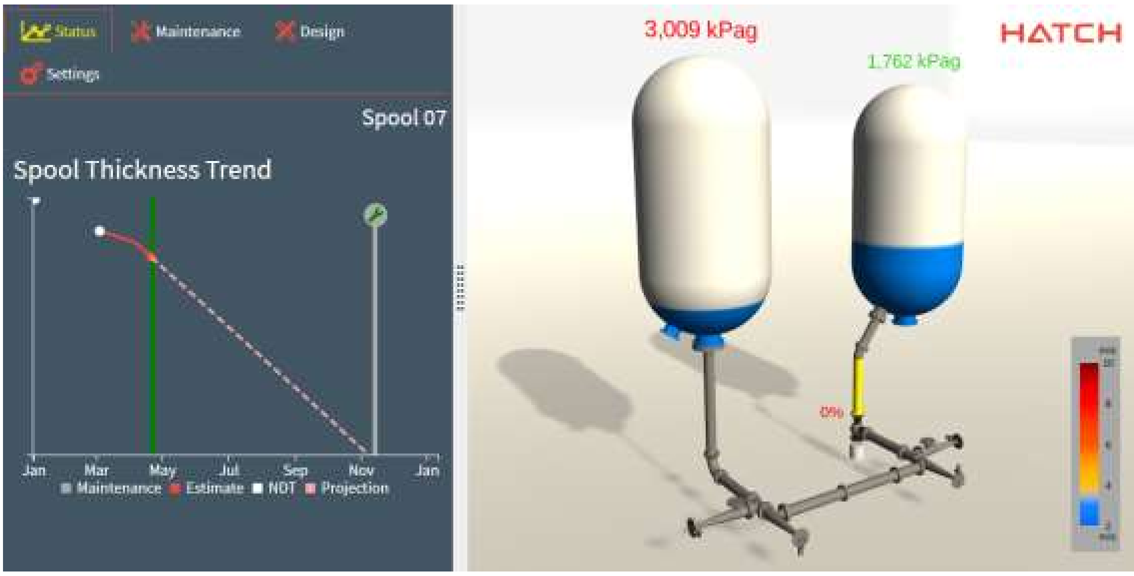

Figure 11. Life projections of piping spool based on current operating mode.

3.5. Short-Term Simulation

Short-term simulation focuses on what-if scenario simulation to help determine the best path forward for a given process constraint or impending change. Previous steps along the Digital Maturity Curve have focused on fully understanding 'what is about to happen?'. At this stage, attention shifts to 'what can I do to avoid it?'.

In discussing simulation at this level of digital maturity, focus is placed on deployment of real-time models, with continual and automated calibration against live plant data. This implies that models are in a perpetual state of readiness, allowing for rapid what-if scenario testing. This concept often considers cloud-based deployment of complex process models to allow for rapid convergence times and the ability to simulate multiple scenarios simultaneously.

A core benefit of deploying such models within a digital twin is the ability to create 'spin-off' parallel instances of the current plant state in which to perform the what-if scenario. Results can then be easily understood and compared against current actual operation.

3.5.1 Application

Utilizing the Digital Asset Model for multi-phase hydraulics between flash tanks, 'spin-off' simulations may be performed. These simulations may manipulate any independent variable, such as digestion feed flow, flash tank pressure profile, flash tank level, level control valve condition/position, or piping component design.

As an example, the hydraulic contribution of the control valve has been assessed. Starting with current operation as per Figure 12, the control valve may be removed from service (simulating 100% open position) and the impact to the hydraulic system integrity may be assessed (Figure 13). In addition, the impact on predicted component life may also be observed.

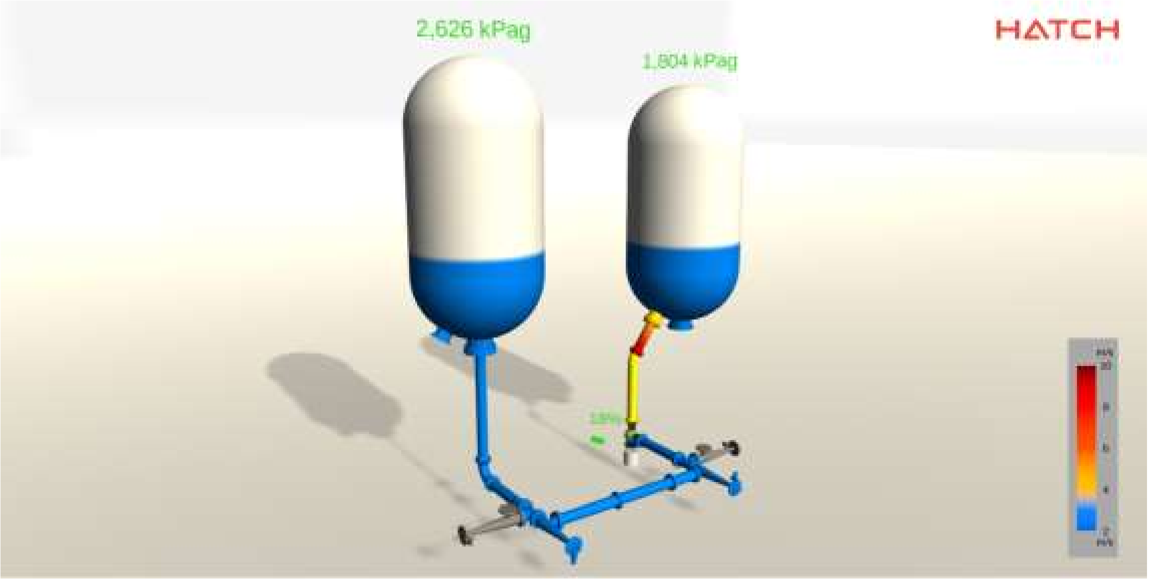

Figure 12. Normal operation with functioning level control valve.

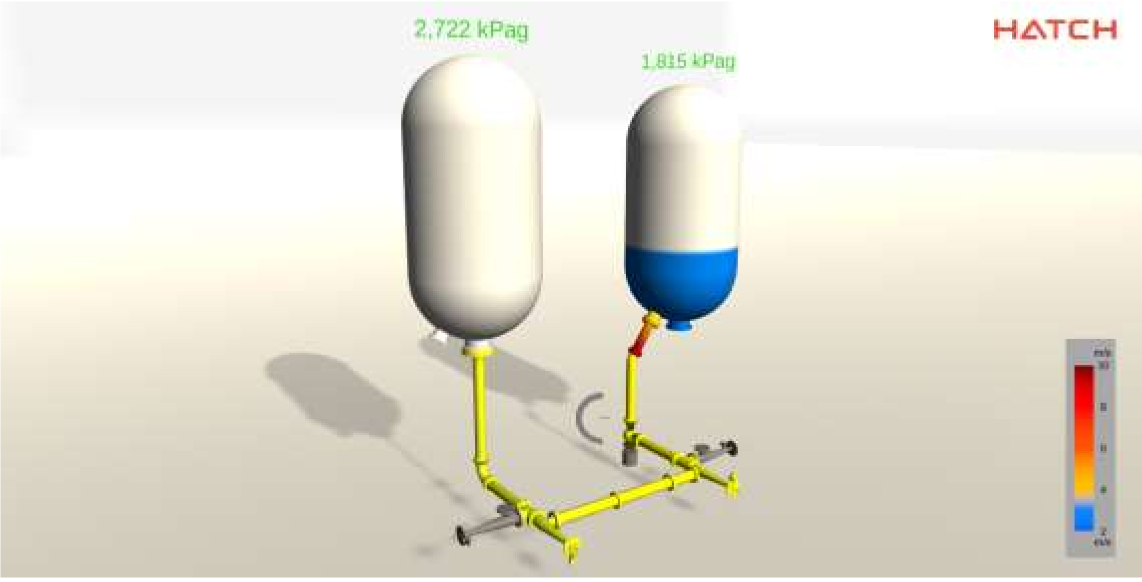

Figure 13. Simulated operation with fully-open level control valve.

This simulation considers the impact on upstream tank level and vapour bypass, as well as the resulting multi-phase flow velocities predicted throughout the piping system. Impact to the predicted life (Predictive Analytics) is also assessed for each piping component. In essence, this simulation allows refinery personnel to quantify the importance of maintaining the level control valve in a functional state, considering the mechanical integrity of the system.

3.6. Optimization Scenario Simulation

This step of the Digital Maturity Curve focuses on the ability to determine the best path forward for a given condition or impending process change. In the alumina refinery setting this may focus on various aspects of the operation and cover various time horizons. Examples may include:

- Equipment rotations: What is the optimal cleaning schedule for a heat exchanger given the expected rate of degradation of thermal performance and considering energy losses, maintenance crew availability and rotations of adjacent equipment.

- Production/quality forecasting: What is the best mitigating measure to take to counteract an impending process change (bauxite quality change, planned maintenance etc.).
- Plant-wide operations: What is the best action to take based on available process levers (plant flow, bauxite charge, digest temperature) and plant constraints (equipment outages, plant bottlenecks, maintenance crew availability, steam supply limits etc.).

There are two common approaches to addressing these questions.

1. The use of discrete scenario simulation. Here, many discrete scenarios are simulated simultaneously and the best course of action for the given objective function is concluded. This method has the advantage of being suitable for highly complex processes. As a downside to this approach, this is effectively a brute-force method that is computationally intensive. While valid for complex processes (such as alumina refining), this approach may not arrive at the true optimal outcome.
2. Mathematical optimization using methods such as linear or nonlinear programming, mixed integer linear programming, constrained optimization, etc. This form of optimization describes and solves the problem and constraints mathematically and arrives at the true-optimal solution. This approach is already widely adopted in some industries, typically for planning & scheduling functions (e.g. maintenance scheduling or logistics plans). A current example includes application in bauxite mining and shipping operations to optimize the mine plan and rail/port functions.

3.7. Production Recovery Optimization

At this level of the Digital Maturity Curve, there is a built-up understanding of how the processing plant functions and, importantly, how the plant will function under different operating scenarios. Production Recovery Optimization aims to utilize this information for some high-value and rapid insights during times of production interruptions.

During an unplanned outage/breakdown, all previous stages of the Digital Maturity Curve are used to determine the best way to recover to the production schedule while avoiding common pitfalls, such as:

- Shifting of bottlenecks to downstream facilities
- Operating facilities/equipment beyond their design envelope, increasing strain or duress and increasing likelihood of additional equipment failures
- Exceeding product quality specifications.

Alternatively, focus may be placed on how to best take advantage of the unplanned downtime/delay. This may identify possible opportunistic maintenance or running under different modes of operation to minimize operating costs etc.

3.8. Product Digital Thread

As a final (but ongoing) stage of the Digital Maturity Curve, the digital thread provides a horizontal slice of the final product and an understanding of exactly where it came from and each of the processes and personnel that contributed throughout its manufacture. This level of digital maturity can generally only be attained once there is a full understanding of the entire product value chain.

For an aluminum value chain, such visibility may be captured on a product/shipment specific basis and include:

- Bauxite mining details, including mined location and ore grade and climatic events during mining

- Shipping and logistics channels from mine to refinery
- Conditions during refining, such as general plant configuration, stockpile blending, equipment status and condition, equipment mode of operation during refining (vs. design operating envelope), final alumina quality attained, etc.
- Key aspects of smelting, including energy supply and auditing details
- Shipping logistics to final customer, including customer contract and market conditions during time of sale.

Ultimately, all attributes of the final product (source, quality, quantity, etc.) are linked to all aspects of its production, enabling macro-scale visibility, analytics and decision-making.

4. Conclusion

An array of modern digital technologies and methods are currently available to help transform the refinery design process, improve productivity of operations, reduce maintenance cost and offer the opportunity to redefine business processes and business models. This paper has introduced the concept of digital maturity to provide a structured approach for considering the application of these tools to assist in the digital transformation of complex processing plants.

The various stages of the Digital Maturity Curve were presented and applied to tackle a common challenge in the pressure letdown area of an alumina Digestion facility. A digital twin was created to centralize the various sources of asset information including live plant data, maintenance & NDT information, design documents, as well as digital tools such as analytics and simulation. Complex two-phase flashing slurry flow models were deployed to provide live instantaneous velocities for each piping component and fitting throughout the slurry piping system. Velocities were shown graphically within the digital twin to provide a simple and intuitive means assessing current asset performance and to help fill a major knowledge gap linking process dynamics and mechanical integrity of the Digestion slurry piping. This information supplemented NDT data to provide live indications of asset health via remaining pipe thickness approximations. Analytics were also applied to produce residual life predictions for each piping component. Finally, simulation capabilities were introduced to enable spin-off "what-if" analyses.

5. Acknowledgement

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