INTELLIGENT ASSET MANAGEMENT

Alesio Lanzara (Australia), Peter Carydias (Australia), Hardeep Dhaliwal (US), and Numan Mir (UK), Wood, set out an end-to-end framework that can help LNG industry operators maximise the value of predictive maintenance and move towards the remotely operated, autonomous plant.

With fluctuating resource prices, a disrupted supply chain, a push for greener, sustainable, efficient operation, and a dramatic up-tick in digital adoption, operators are being challenged to dramatically reduce operating costs (40%), site staffing (60 - 80%), emissions (net zero), and safety incidents (zero).

Furthermore, they are being tasked with accomplishing this while simultaneously improving production throughput and availability (plus 10%).

From Wood's asset lifecycle experience across multiple sectors and geographies, and more formally through its 2022 Global Survey, the company has identified six steps that will strongly influence the successful design and implementation of impactful predictive maintenance at scale.

Step 1. Clearly articulate a specific plant business case

In a competitive commodity market, industrial operators are setting ambitious transformational agendas to move their businesses into the digital age. In fact, 60% of companies Wood surveyed are undergoing significant business transformation over the next five years targeting the following areas.

- Targeting up to 10% uplifts in production from the same assets.
- Decreasing operating costs by up to 40%.
- Targeting zero safety incidents and net zero emissions.

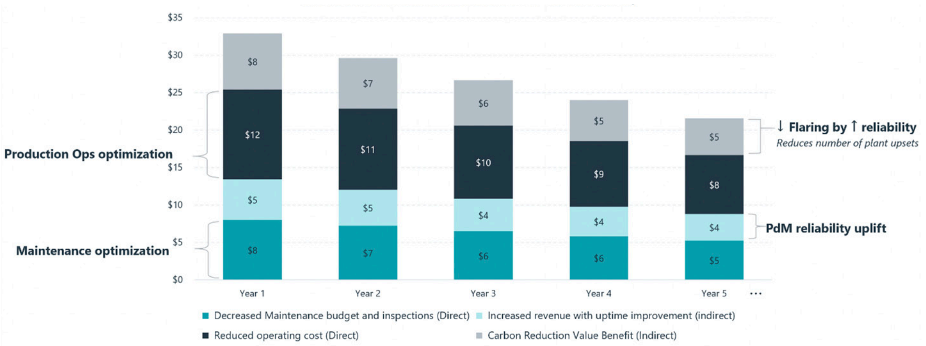

Figure 1. LNG train transformation discounted benefit of approximately US$300 million over 25 years. Plant size = approximately 5 million tpy, maintenance budget = approximately US$20 million/y, operation budget = approximately US$30 million/y, 0.25 million t CO_2e/y from flaring, 1.25 million t CO_2e/y from gas turbines, average CO_2 price of US$60/t, assume approximately 70% of flaring is due to unplanned flaring, assumed plant is 95% reliable, average LNG price of US$8/million Btu.

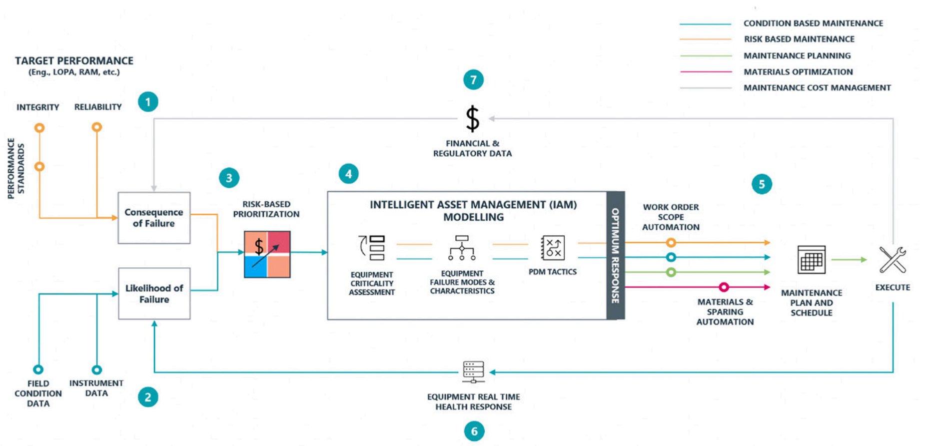

Figure 2. Shifting to dynamic operating and maintenance strategies to continuously optimise throughout the asset's life.

Understanding the value basis of the transformation through a comprehensive business case is essential to identify and realise the full value of a transformation.

Independent project analysis has identified that a staggering 43% of the sanctioned project value is typically lost over the life of oil and gas projects, approximately 70% of this (around 30% of NPV erosion in total) due to production shortfall.

Wood conducted surveys and operational analysis of two main project phases to reveal major drivers of value erosion and identified which can be mitigated at scale.

Commissioning and early-stage operations

Wood's research suggested that approximately 66% of early-stage operations issues can be identified and resolved through robust data-driven maintenance techniques, having a direct impact on production.

The company's experience with clients reveals that small-bore piping, mechanical seals, thermowell failures, as well as generic strategy application and poor predictive maintenance setups round up the top 10.

Due to the transient and dynamic nature of operation, a large breadth of failure modes will be experienced. This presents both an opportunity for mitigation via tactical deployments of sensors and models, as well as the measurement and storage of the failure data for training and validation purposes.

Steady-state operations

Rotating equipment is the number one source of production deferments (approximately 60%), maintenance (approximately 21%), and carbon emission intensity (approximately 65%).

Compressors, turbines, pumps, valves, and instrumentation rank poorly across both an analysis of production deferment and maintenance intensity, with typical maintenance profiles revealing an increase in maintenance backlogs and forelogs, a sign of an organisation in a reactive state, both from strategy and maintenance response.

Typically, critical pumps and instrumentation are designed to have significant redundancy to maintain plant and system level reliability, so it is not expected to see impacts of this magnitude at plant level, pointing to maintenance execution and backlog challenges.

There is a clear dynamic interplay between production trips or deferments and emissions intensity, as McKinsey identifies approximately 70% of flaring related emissions are due to trip/failure events.

Taking these inputs, Wood estimates the predictive maintenance business case to be worth a discounted value of US$300 million over 25 years for an LNG plant producing 5 million tpy, as outlined in Figure 1.

Step 2. Set up a dynamic philosophy, system, and organisation

Wood has found that typical asset management setups are not initially configured to take advantage of the latest technology and data streaming from operations; for example, in the company's approach, sensor data directly driving resourcing and inventory management decisions.

Modules are operating independently, aligned with functional silos, and there is a gap in the understanding of the optimisation needed to achieve greater asset performance.

The data used to simulate system performance is usually from generic data sources e.g., OREDA with various assumptions baked in. This is often justified based on the belief that predictive analytics models need time to learn in operations before being productive.

And there is a lack of attention to organisational context used to support the data, such as the asset management maturity, the type of maintenance strategy used, the utilisation of equipment, the organisational setup, and the nature of the vendors and manufacturers involved.

This does not adequately prepare assets for the range of potential issues that can be experienced through these stages and where optimisation opportunities lie.

Wood recommends leveraging information collected from existing operations and industry knowledge bases to initialise models to detect component failure.

Understand how a production operations asset creates value from its operations, maintenance, and supply chain functions

By mapping out the current processes across the intelligent asset management opportunity space, Wood's workflows reduce the time to insights and close loops in organisational processes to bring returns with reduced need for human capital.

Once the appropriate scenarios have been accounted for, models can be configured for operational deployment to process live dynamic inputs from PdM models summarising component reliability statistics and predictive maintenance model outputs, aggregated to the equipment, system, plant, and organisational level. Feeding PdM models as input allows the ability to uncover opportunity to debottleneck and improve availability in real-time.

Feed this back into the next capital project to establish a competitive advantage in project selection.

For example: reliability, availability, and maintainability (RAM) models taking into account differences in operations throughout the stages of the project lifecycle e.g., start-up/early stage operations, steady-state and end-of-life, and sensor and field data driving resourcing and inventory management decisions.

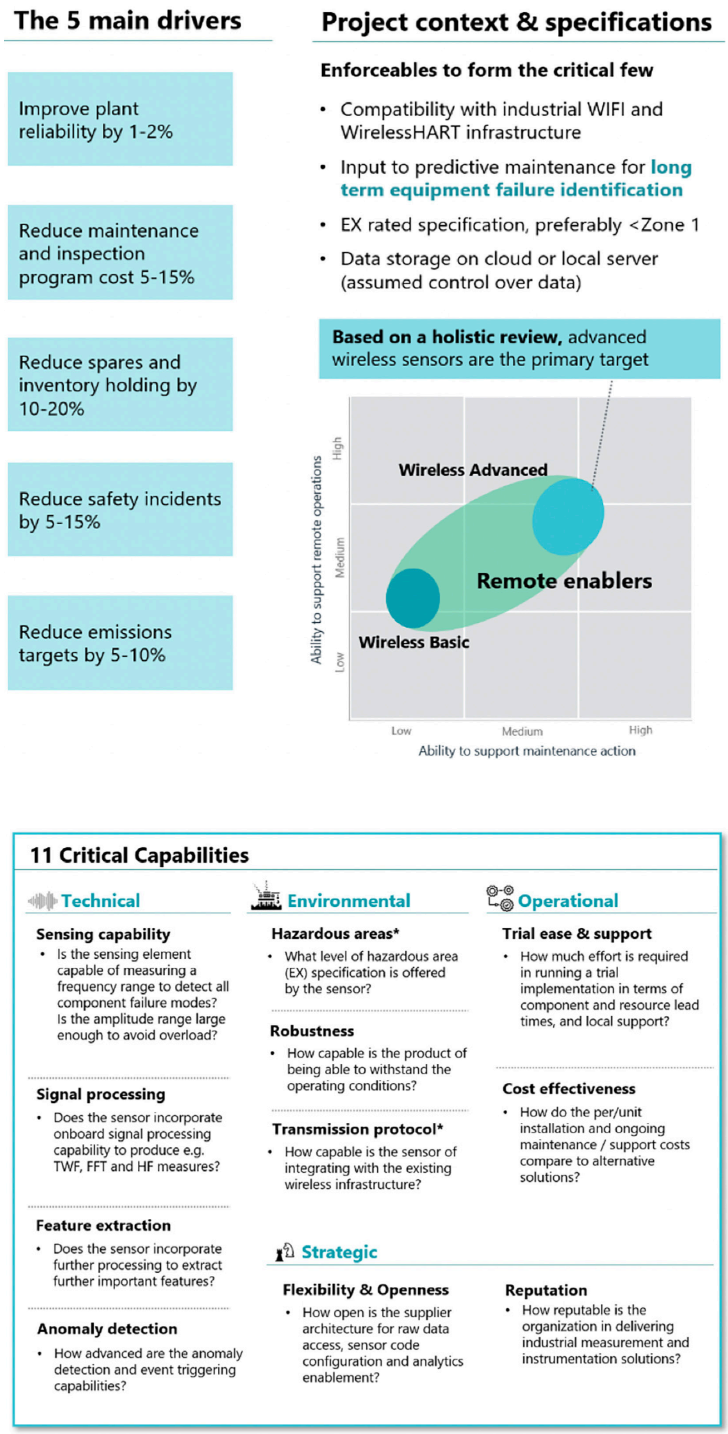

Figure 3. Techno-economic assessment example enabling robust operational technology (OT)/information technology (IT) infrastructure cost sizing and contract negotiating power with vendors.

Step 3. Be proactive with operating technology infrastructure and data strategy

Once the commitment to a high-value business initiative has been made, it is critical to define data types, bandwidth, latency, and mobility requirements to unlock step-out operational performance.

This enables robust operational technology (OT) and information technology (IT) technoeconomic assessments, including infrastructure sizing, organisational structures and competencies, and productive contract negotiation with vendors.

For instance, for a set of rotating equipment for an industrial plant, Wood has identified the following critical failure detection parameters that are required.

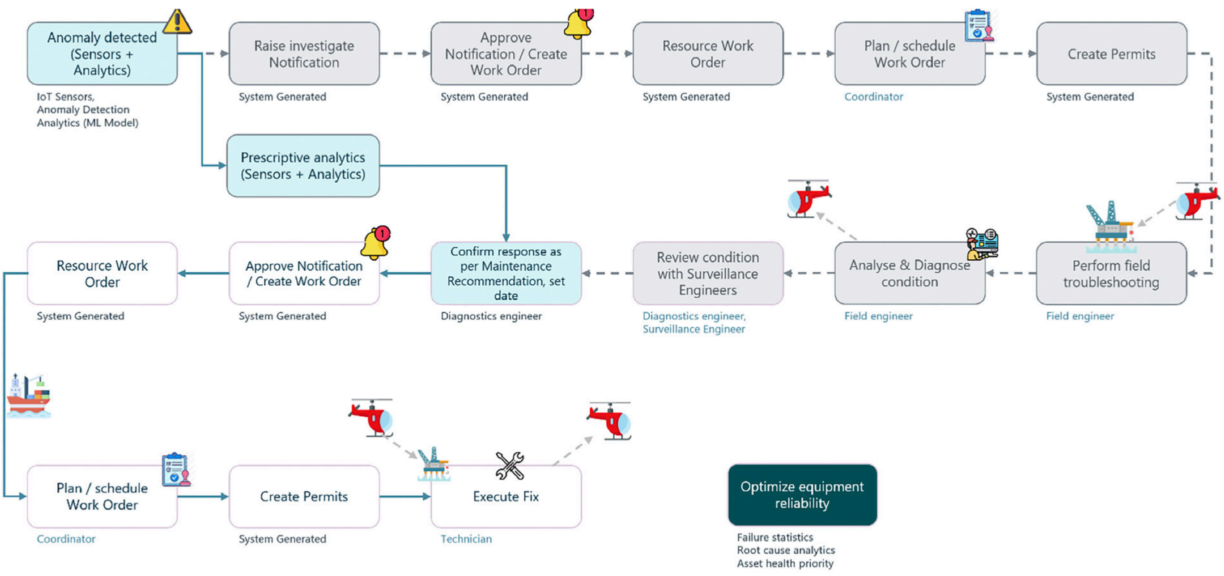

Figure 4. Design the level of decision-making speed into the process to clearly understand system detail and requirements.

Vibration

Approximately 70% of equipment failure components can be identified from analysis of the detailed time-waveform (TWF) and frequency spectrum, with potential failure (P-F) horizon lead times of six to 12 months in most cases. Measurements taken across the machine in displacement, velocity, and acceleration reveal machinery dynamics and behaviour. A dense vibration sample can contain up to 1 Mb per measurement point (analogous to an audio file), which forces a trade-off between transmission rates, sensor battery power, and the OT infrastructure to support this.

Fuel and lubricants

Monitoring critical fuel and lubricant parameters can assist with identifying root causes of tribological and performance-related issues e.g., viscosity and water content, as well as serving as a secondary diagnostic parameter to identify failures through oil debris analysis. Given that an oil sample can contain as many as 25 parameters that require separate test methods, fixed sensors focusing on contamination control could be very cost effective, given it is a root cause of >80% of tribological failures. Each of these parameters are typically floating point, therefore including sample sizes up to 50 bits.

Performance

Detailed equipment parameters such as flow, pressure, temperature, power, speed, and current are used to inform thermodynamic modelling that can improve both top-line operational performance (overall power output, throughput), efficiency (emissions, fuel consumption), and maintenance (filters, water-washing, seals). Like the parameters for fuel and lubricants, these typically each consist of sample sizes up to 50 bits.

Visual imaging

Images or videos of the equipment have traditionally been taken by operators and maintainers through daily patrols or rounds – to inspect operating equipment where there are monitoring technology gaps as well as conducting changeovers, etc. However, with increasing automation, footage can be captured via fixed CCTV cameras or other in-field mobility solutions. A 1080 p compressed image size is approximately 0.5 MB (4 Mb), and similarly to the vibration data, for the purposes of targeted predictive maintenance will not be required at high frequencies, especially with other available information.

An understanding of optimal data collection parameters required to implement PdM workflows informs an optimal technology strategy regarding the adoption of sensors and overarching IT/OT infrastructure (e.g., private LTE/5G in high-value mobile use cases, the expansion of industrial Wi-Fi, or extended use of wireless sensor networks such as WirelessHART). This will directly influence the direction of travel for vendors of both sensors (e.g., ensuring the communication protocol is covered) and equipment (e.g., ensuring proper sensing coverage) to unlock value and satisfy operators in the resources sectors.

Step 4. Develop low-touch strategies that optimise for availability, reliability, staffing, and inventory

Wood has implemented several smart, low-touch strategies across energy and resource clients, which enable remote operations, while optimising for production availability, reliability, as well as spares and inventory, safety, and emissions.

For example, gas turbines account for up to 65% of the emissions from an LNG plant, from liquefaction and power generation, and contribute to trip-related flaring, with 70% of flaring emissions due to non-routine and trip events.

A 1% efficiency gain from the gas turbine fleet will reduce overall plant emissions by 0.7% and fuel gas usage by 1%. For one client, Wood configured their fleet to run closer to full load, with the addition of a battery to help with spinning reserve. This increased efficiency by 5 - 10%, and reduced fuel gas spend by the same margin. The company also implemented models that prescribe the optimal timing of water washing and filter change-outs, and predict instrumentation, sensor, and component issues through predictive modelling of critical performance parameters.

End-to-end system design

Figure 3 outlines a high-level, end-to-end process flow, and the interfaces between a system engineer responsible for maintenance strategy, a diagnostic engineer responsible for equipment surveillance and troubleshooting, and the maintainer responsible for planning, scheduling, and executing the work. The intent is to solve for the entire process, as opposed to focusing on either sensors or anomaly detection models.

Through both focused interviews and operational analysis, Wood has identified that implementing new sensor technology, manual monitoring techniques, and diagnostics will not translate into value if there are resource or parts availability constraints, or if clients have a large existing backlog of maintenance or lack effective PdM- or CBM-based risk and task prioritisation processes. To overcome this, the company provides optimised end-to-end approaches to managing compliance to performance standards, utilisation of operators and maintainers, allocation of inventory, centralised engineering troubleshooting efforts, and prioritisation of the maintenance backlog.

Table 1. Optimise end-to-end, sensor-to-action workflows with the necessary objectives and key results

	Objective	Potential key results	Impact
Model is reliable and resilient	Maximise model reliability – able to be used when required (data pipeline).	99% reliability, boundary drawn around model.	1% reliability gain approximately US$1 million in throughput.
Model outputs are explainable	Not a black box. Ensure model outputs and form are explainable and logical.	>90% accurate prescriptive recommendations. FP/FNs are explainable.	Two to three times faster cycle times.
Model maintains high performance	Maintain high model recall, specificity, and computational efficiency.	Maintain >95% recall, >90% specificity.	5% recall gain = US$3 million through plant reliability. Approximately US$10 000 for each site investigation.
Model is scalable and flexible	Fleet-learning/master model approach. Easily integrate additional sensors, machines, and changing components.	80% of models are fleet-learning (e.g., pumps, compressors, conveyors, etc.)	Tag-specific approach could cost approximately 50 times more to manage.
Customer experience	Ensure the wide adoption within the business process, with good feedback from users and owners.	95% adoption for target audience, integration within key business process. 9+ net promoter score, monthly feedback.	2 - 3% reliability improvement. 10 - 20% cost reduction.

Step 5. Optimise end-to-end sensor-to-action workflows with the necessary objectives and key results

For automated or low-touch strategies to work effectively and to be readily adopted within the workflow, availability, reliability, staffing, and inventory targets will need to be translated to PdM model performance and explainability to support the actions performed.

The company has noted that several providers may focus on offering a shell platform but may not anchor on optimisation and maintaining high performance. This is an important consideration as, for example, a 5% difference in one performance measure, recall, could be worth US$3 million/y in missed equipment failures.

The resources sector has been experimenting for approximately the past five years on what is required to embed new technology such as artificial intelligence (AI; e.g. deep learning, deep reinforced learning, technical language processing) into business workflows.

Wood considers the following five AI key success attributes to be essential:

- Model reliability and resiliency: Essentially, whether the model and overall solution can be used when required. Upfront agreement on the entire data pipeline reliability, availability, and maintainability requirements will invite scrutiny and hardening on elements that do not meet expectations. This could come from the IoT sensor, the network connectivity, database updates, or latency issues in front-end refresh rates if the system is near real-time. Currently, most industrial wireless applications are used for monitoring purposes, however factoring in bridging requirements for open-loop or closed-loop automation systems and interfacing between OT/IT will highlight key questions in design.
- Model explainability: The primary barriers to the uptake of AI techniques within the resources sector are inability of the models to explain their outputs and optimise these apart from observing more failures, which is contradictory to the business' objective. Taking a hybrid modelling approach by combining the benefits of machine learning (statistical processing), with physics-based models and codified decision logic is integral to industry adoption. A clear articulation of the inherent limitations of the model will also help clarify objectives and force a robust discussion with engineers on how best to use the solution.
- Model performance: This refers to the model's ability to achieve and maintain a high recall (e.g., >98%), specificity (e.g., >90%), and computational efficiency under a diverse set of failure modes and scenarios.

- Model specificity is set to reduce the number of false positives which the system generates, which leads to complacency or lack of urgency as advisory alerts are generated and, in the worst case, leading to excessive and wasted resource spend on field troubleshooting.
- Model recall is set to reduce the number of false negatives (or missed failures) that the system generates and is the primary reason the model exists. For critical systems, it is necessary to focus on this firstly, to boost confidence in the technical engineering team's ability to adopt this into their daily workflow.
- It is possible to achieve extremely high scores for each of these aspects, by making critical design decisions on the model form. E.g., by boosting ML algorithm selection with a series of codified decision logic, emulating a domain expert's thought process, Wood has obtained scores which far exceed traditional neural network or black box AI approaches, with the added advantage of the model being explainable.

- Model scalability and flexibility: As the solution is built, it is essential to ensure that the prescriptive maintenance framework can scale – as new sensors are added, more failure modes are identified, and additional componentry is added across the technology landscape. Adopting fleet-learning models is the recommended approach, allowing for a centralised, master model for an equipment type as opposed to many thousands of models customised to each sensor or equipment installation. Not only would the latter approach render ongoing maintenance a nightmare, but it would not take advantage of cross-asset learnings for failure modes, for example.
- Client experience: Wood embeds key results to understand integration with the business processes, user adoption, and scaling in reference to daily, weekly, and monthly workflows, as well as technical standards, guidelines, and procedures – proof that the solution has the technical team's sponsorship. For solutions configured with end-to-end automation in mind, six-month model reviews with human-in-the-loop feedback could be required for technical authority buy-in as engineering standards are updated to reflect this.

Step 6. Partner with specialists who focus on results and are accountable

For asset operators looking to benefit from a PdM programme, the right specialist solution partner can accelerate success by bringing proven approaches, models, and frameworks from early project design to continuous asset performance optimisation. Look for:

- Complete capability: Ability to integrate PdM and intelligent asset optimisation across an asset's lifecycle, technical depth on selection, evaluation, and adoption, and the technical competency to work with and influence technical authorities on technology selection, evaluation, and adoption within the business.
- Flexibility in approach: The ability to influence strategy optimisation, configure a solution within an existing technology landscape, and to support staff on reliability improvement and defect elimination processes to solve engineering problems on the plant.
- Quantitative accountability: Service-level agreements and commercial models that incentivise a focus on results (both solution use and adoption, as well as improved asset performance) as opposed to just upfront implementation, licencing, and product subscription fees. The intended benefits of these solutions to justify the cost and transformation focus needs to remain front and centre.

Conclusion

As asset operators look to transform their organisations to achieve greener, more sustainable, and step-out performance, this six-step framework will accelerate the integration of new technologies in the design and implementation of impactful predictive maintenance at scale. **LNG**

Note

This article was based on Wood's webinar entitled 'Predictive maintenance: Towards the remotely operated, autonomous plant'.