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DOI: https://doi.org/10.64388/IREV10I3-1722968

AI-Enabled Predictive Maintenance of Wellhead and Pressure Control Equipment in Upstream Oil and Gas Operations

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Abstract—The oil and gas wells which are operated in the upstream sector depend on wellhead and pressure-control equipment in order to maintain pressure inside acceptable limits, to regulate the production of multiple phases, and to isolate the well should the operating limits be exceeded. Because failures may take place in the production chokes, in the master and wing valves, in the surface safety valves, in the actuators, in the seals, and in the pressure monitoring equipment, such failures can result in a slowdown of production, a loss of containment, or an emergency shutdown. This review analyses in detail how artificial intelligence is able to transform the maintenance of such assets from one that is based on scheduled inspections and corrective repairs to one that is based on the current condition and is capable of making predictions. In order to answer four closely related questions the body of literature published between 2020 and 2025 was compiled: what failure mechanisms give rise toward observable data signatures; which machine-learning, deep-learning, probabilistic, and hybrid methods are suitable for carrying out anomaly detection, diagnosis, health-index estimation, and prediction of remaining useful life; what limits the application of these methods in practice; and how the predictions should be incorporated into operational and maintenance decisions. Evidence from studies on wellhead choke modelling, subsea valve prognostics, petroleum machinery, SCADA anomaly detection, pump predictive maintenance, and digital-twin research shows that the greatest real benefits are not due to any single algorithm but result from combining reliable sensing, knowledge of the operating mode, time-aware features, uncertainty estimates, and engineering constraints. Ensemble models work well with structured and noisy field data, whereas temporal deep-learning methods are useful when high-frequency historical data and representative failure cases are available. Investigations into valves with small sample sizes have shown the advantages of using probabilistic and data-model linked prognostics, and digital twins provide a way of continuously aligning asset physics with data-based intelligence. The review proposes an asset-centred deployment architecture in which detection, diagnosis, prognosis, risk ranking, and maintenance planning form a closed loop. The research priorities are the development of standardised failure taxonomies, cross-field validation, physics-informed learning, uncertainty-aware remaining life, explainable alarms, and prospective field trials that focus on safety outcomes, the avoidance of production deferment, and improvements in maintenance efficiency instead of on accuracy alone.

I. INTRODUCTION

The wellhead assemblies constitute the pressure boundary between the producing reservoir and the surface production system, and the valves, chokes, actuators, seals, fittings, and transmitters involved have to work reliably within environments involving high differential pressure, changing flow conditions, corrosive fluids, solids, scale, vibration, thermal cycling, and frequent variations in operating conditions; a choke which erodes internally might still appear mechanically sound even if its actual flow area has changed; a gate or seat may fail to maintain its seal without showing any obvious external signs; an actuator may develop stiction or respond slowly; and a pressure transmitter may drift so gradually that a normal alarm will never detect the developing fault. Because these components affect both production control and the integrity of the barrier, decisions about maintenance should consider not only the availability of the equipment but also process safety and the possible consequences of an incorrect intervention.

The volume of information available to assist with these decisions has grown as a result of digitalisation. Current production systems keep records of wellhead pressure and temperature, downstream pressure, choke position, valve commands and feedback, flow estimates, alarm histories, vibration or acoustic measurements where the equipment is fitted with such devices, and upkeep records through the use of SCADA, historians, and dedicated monitoring systems. At present, research within the oil and gas industry is using artificial intelligence (AI) and machine learning (ML) in order to convert this wide range of information into forecasts, classifications, and recommendations for decision-making. There is especially great interest in the field of predictive maintenance (PdM), the aim being to go further than just identifying a failed asset by detecting deterioration at an early stage so that an economically and operationally appropriate response can be planned. Reports on petroleum machinery highlight fault diagnosis and the prediction of remaining useful life (RUL) as the two key components of model-based prognostics and health management.

It is by no means simple to apply general AI capabilities to wellhead maintenance. The data obtained from wellheads is greatly affected by the production operations: changes in pressure can be caused by reservoir depletion, separator backpressure, intentional adjustments of the choke, restart transients, chemical treatment, or actual deterioration of the equipment. As failure events are rare in comparison to normal operation, the labels are usually incomplete and the equipment designs vary from field to field. AI models which do not take these factors into account may end up learning about operating practices instead of the physics of degradation. Moreover, the literature on SCADA and industrial AI shows that data quality, synchronization, interpretability, and integration alongside existing operational technology are just as important as the choice of model. Hence, a high classification score on an offline dataset does not provide sufficient evidence for safe use in field maintenance.

The aim of this review is to give a critical summary of the most recent evidence on the application of artificial intelligence in the predictive maintenance of wellhead and pressure-control equipment, and to create a framework that is geared towards pragmatic implementation through integrating failure physics, sensor data, AI outcomes, uncertainty, and the maintenance actions carried out. The review is based on four specific objectives. The first of these is to determine the primary failure mechanisms and the data patterns which plausibly indicate degradation in chokes, wellhead valves, surface safety valves, actuators, seals, and pressure instrumentation. The second objective consists of comparing the different AI methods employed for anomaly detection, fault diagnosis, health-index development, and remaining useful life estimation, while taking into account the typical data limitations encountered in upstream operations. The third objective is to examine the various limitations involved, such as small sample sizes, class imbalance, non-stationary operating conditions, the requirement for explainability, the ability to generalise, integration with SCADA systems, and the issues connected with safety assurance. The fourth objective is to propose a closed-loop architecture and a research programme for field validation. Unlike other more general reviews of AI in the oil and gas industry which cover areas such as exploration, reservoirs, drilling, production forecasting, and sustainability, this review focuses on the equipment in question. It also builds on previous work that has been concentrated on pumps by instead concentrating on the surface pressure-control system, since in this case the process behaviour and mechanical integrity are closely related.

II. REVIEW METHODOLOGY

A structured integrative review was selected because the available evidence consists of reviews, field studies, equipment-specific prognostic models, digital-twin research, and methodological papers that all work with different datasets and performance criteria. The search period was restricted to the years 2020 to 2025 so as to include the period during which industrial IoT, SCADA analytics, ensemble learning, deep temporal models, and digital twins became significant in research concerning upstream production. The search terms combined words associated with predictive maintenance ("predictive maintenance", prognostics, RUL, fault diagnosis, anomaly detection, health index") with equipment terms (wellhead, choke, Christmas tree, surface safety valve, subsea valve, pressure control, actuator, production valve) and AI terms (machine learning, deep learning, ensemble learning, digital twin, physics-informed, explainable AI). Studies involving petroleum machinery and pumps were included provided that the methods they used addressed transferable issues such as sparse failure data, noisy SCADA data, temporal labeling, or RUL prediction.

The sources that were considered eligible were peer-reviewed journal articles written in English, conference papers which presented clear technical methods, and systematic reviews published within the specified period. A study was included only if it concerned upstream production equipment, wellhead flow-control behaviour, asset-integrity monitoring, or a prognostic methodology that could be directly applied to pressure-control assets. Exclusions were applied to studies that were entirely about the reservoir and contained no element relating to equipment maintenance, to those that concentrated solely on the downstream aspect and did not include any transferable condition-monitoring content, to non-technical commentaries, and to any publications outside of the specified time frame. Thirty core sources were selected for the critical synthesis. Reviews on petroleum and AI as well as IoT provided the digital context; the studies on chokes and valves gave asset-specific evidence; the predictive-maintenance studies involving petroleum pumps and field equipment were used to guide the model and deployment decisions; and the studies on digital twins, SCADA, and physics-informed methods assisted with the integration procedure and the analysis of future research.

The way in which the synthesis was organised was according to engineering function and not simply on the basis of the algorithm. For each source, consideration was given to the type of asset, the mechanism of failure or degradation, the input data, the learning task, the validation method, the reported limitations, and the capability of maintenance decisions. This method avoids a common defect of reviews that focus on algorithms, which is to compare different methods without taking into account whether the target labels correspond to actionable failure states. Because there were considerable differences between the datasets in terms of the definitions of failure, the sampling rates, the operating conditions, and the evaluation criteria, a statistical meta-analysis was not carried out; instead, the review makes use of comparative qualitative synthesis and some of the results that have been reported in order to assess where the evidence is consistent, where it is still particular to the asset, and what is required before a model can be trusted as part of a pressure-control maintenance workflow.

III. WELLHEAD AND PRESSURE-CONTROL EQUIPMENT AS A PREDICTIVE-MAINTENANCE PROBLEM

The maintenance issue starts with the physical performance of the equipment. A production choke serves to reduce pressure and controls the flow by means of a restricted shape. The deterioration of such a choke may result from particle erosion, cavitation-like effects, corrosion, deposition, or mechanical wear. Research into chokes based on data shows that process measurements are able to capture complex relationships which cannot easily be expressed using empirical correlations alone. Jahren et al. used data from first-principles simulation to model choke erosion. Alarifi constructed machine learning models using more than four thousand field production tests for critical and subcritical multiphase flow through wellhead chokes, proving that surface variables which are readily available can beat out conventional correlations when it comes to estimating flow. Even though accurate flow prediction is not in itself a maintenance activity, a continuous discrepancy between the expected and the actual behaviour of the choke can become an indication of degradation provided that changes in operations and in the fluid properties are taken into account.

Recent research has reinforced this link. Dabiri and colleagues applied machine learning to model the rate of liquid flow through wellhead chokes and showed that the conditions at the wellhead and the variables associated with the choke contain enough information for accurate nonlinear prediction. Kaleem and co-workers found that hybrid ensemble methods can improve the forecasting of multiphase flow through surface chokes and are able to rank the impact of the production-control variables. With regard to maintenance, the key point is that a model calibrated to represent normal choke behaviour can function as a soft sensor: a growing difference between the predicted and the actual process response may signal a change in the effective choke area, erosion, blockage, or a sensor bias. In the case of high-pressure, high-temperature gas service, Alfrayan and others focused specifically on choke erosion using machine learning, thus showing the move from performance modelling to degradation prediction.
The prognostic problem associated with wellhead and Christmas-tree valves is different since their most important function is isolation and sealing rather than continuous throttling. The ways in which these valves can fail include internal leakage between the gate and seat surfaces, leakage from the stem or packing, degradation of the actuator's hydraulic or pneumatic components, stiction, incomplete travel, error in the position sensor, and erosion or corrosion of the components that contain pressure. Direct labels of failure may be rare since safety-critical valves are inspected or replaced before they suffer catastrophic failure. As a result, it is difficult to estimate remaining

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DOI: https://doi.org/10.64388/IREV10I3-1722968

useful life, although studies of subsea valves do provide useful methodological evidence. Shao et al. combined a dynamic Bayesian network with Kalman filtering in order to predict the remaining useful life of subsea Christmas-tree valves while taking into account both measurement noise and parameter uncertainty. A later approach that linked data with a model used short, intermittently sampled monitoring histories to build a health index and then connected this index with Weibull reliability for the purpose of estimating remaining useful life for subsea valves. These studies are especially relevant to wellhead pressure-control equipment since they demonstrate that prognostics can be developed even when degradation histories are limited, as long as physical knowledge and uncertainty are taken into account.

Pressure transmitters and actuators also introduce possible failure modes relating to instrumentation and control. Pressure drift, restriction in the impulse line, intermittent communication, calibration error, or range saturation can all corrupt the variables upon which both the operations and the AI rely. Similarly, delayed or incomplete valve response may result from actuator friction, seal leakage, problems with the supply pressure, or degradation of the solenoid. It therefore follows that a useful predictive maintenance (PdM) system should not regard every abnormal pressure pattern as indicating a mechanical failure. Instead, the command-versus-position mismatch, the valve travel time, the pressure response following a commanded movement, the redundancy existing between the upstream and downstream transmitters, and agreement with flow behaviour all need to be examined together. The literature on the Internet of Things stresses that while field sensing increases the amount of data available it also brings with it concerns regarding communication, interoperability, maintenance, and cybersecurity. For this reason, the mapping of failures to data in Table 1 separates out physical degradation, the observable signatures, and the AI task most suitable for each condition.

Table 1. Failure-mode-to-data map for wellhead and pressure-control equipment.

Asset / failure mode	Physical mechanism	Observable signatures	AI task	Maintenance implication
Production choke - erosion	Sand/solids impingement; trim wear	Pressure-flow residual grows; same opening gives altered ΔP/flow; sand exposure	Healthy-behaviour residual; regression + anomaly detection	Inspect trim; estimate erosion rate; plan choke replacement
Choke / flow path - restriction	Scale, wax, hydrate or debris deposition	Rising ΔP; falling inferred area; temperature/context shift	Change-point detection; classification	Chemical treatment, warm-up, cleanout or inspection
Master / wing / SSV - internal leakage	Gate/seat damage, erosion, debris	Failed leak test; pressure equalization when closed; abnormal decay	Probabilistic diagnosis; health index	Barrier test; repair/replacement based on criticality
Valve actuator - stiction or degradation	Seal wear, friction, supply or solenoid weakness	Longer travel time; command-position lag; incomplete stroke	Time-series anomaly; fault classification	Functional test; service actuator before demand failure
Pressure transmitter - drift/plugging	Calibration drift, impulse restriction, sensor aging	Bias against redundant tags/model; slow response; inconsistent gradient	Sensor validation; drift detection	Calibrate, flush impulse path or replace transmitter
Seals / packing - degradation	Wear, pressure/thermal cycling, corrosion	Fugitive leakage; pressure decay; increasing intervention frequency	Risk scoring; survival/RUL model	Targeted inspection and seal replacement

IV. AI-ENABLED PREDICTIVE-MAINTENANCE PIPELINE

A necessary requirement in this situation is to have a solid data foundation. The fact that SCADA tags may have different sampling intervals, dead bands, engineering units, time stamps, and periods during which data is missing means that maintenance logs could record the replacement of a 'valve' without indicating whether the cause had been seat leakage, actuator failure, or a planned overhaul. The raw data must therefore be synchronized, have its quality checked and flagged, reconciled with work orders, and separated according to operating mode before model training is carried out. Industrial big-data studies have identified missing values, inconsistent formats, the integration between different platforms, and governance as continuous barriers to reliable analytics. In the upstream systems, mode segmentation is essential because the normal characteristics change during startup, shut-in, ramp-up, steady production, well testing, and chemical treatments. A model that is primarily based on data from steady production could incorrectly regard a restart transient as a fault.

Feature engineering must link the way the sensors behave to the degradation mechanisms. Although static values—like upstream pressure, downstream pressure, temperature, choke opening, and flow—are useful, temporal features usually include more information that is relevant to maintenance. Features such as moving averages, slopes, variances, pressure-drop ratios, valve travel time, command-position lag, the rate of change after the valve is actuated, and the residuals from a model that represents normal performance can show a slow deterioration. The literature concerning petroleum machinery also recommends combining subject-matter knowledge with signal processing and learned representations in order to carry out diagnosis and to estimate remaining useful life. With regard to field data from electric submersible pumps, the use of time-aware rolling features and trend-based labels has improved the depiction of the transition from stable to unstable operation. The same principle can be applied to a choke whose pressure-flow relationship changes gradually or to an actuator whose travel response slows down before it fails a functional test.

When choosing a model, one should consider the maintenance issue. For structured tabular data and a moderate sample size, techniques such as Random Forest, gradient boosting, XGBoost, CatBoost and support-vector methods are attractive since they can model nonlinear interactions without needing the large quantities of data that are required by deep networks. Numerous overviews of the petroleum industry consistently show a heavy reliance on ensemble methods for classification and prediction. In their study of field equipment, Wang et al. combined expert rules, support-vector modelling and ensemble techniques in order to classify the condition and estimate the remaining life, attaining an accuracy of 0.98 using data from production well equipment. Similarly, the work carried out using CatBoost for ESP demonstrates how effective ensemble learning can be even when working with noisy and imbalanced SCADA histories, as long as the preprocessing and the domain-informed labelling are carefully designed. Ensemble methods are appropriate to use as an initial approach in the case of wellhead predictive maintenance when the number of failure cases is in the tens or hundreds rather than in the thousands.

If there is a lack of failure data, unsupervised and semi-supervised methods are useful. Methods including Isolation Forest, one-class models, autoencoders, clustering, and probabilistic models of normal behaviour can learn the boundaries of normal operation and signal deviations for further investigation by engineers. Wadinger and Kvasnica developed an adaptable and interpretable approach for detecting anomalies in SCADA-based industrial systems which learns the dynamic operating limits and identifies the inputs that are causing the anomaly. Since interpretability is important at the wellhead, an alarm that simply states 'anomaly score 0.91' does not give a clear reason for taking action; a more helpful output would be one that says the relationship between upstream and downstream pressure is abnormal at the current choke setting, or that the valve travel time has increased even though the actuator supply pressure is normal.

Temporal deep learning works particularly well when dealing with long sequences that have a high frequency. Recurrent neural networks, LSTM architectures, temporal convolutional networks, attention models, and Transformers are capable of learning degradation patterns that evolve over time. In the context of research into the remaining useful life of drilling pumps, convolutional feature extraction has been combined with attention and

Transformer techniques in order to capture both time and time-frequency information. Likewise, general reviews of RUL indicate that deep methods can learn rich representations but do require representative historical data and careful attention to overfitting. Since data is often scarce, together with changes in operating conditions and limited failure diversity, simpler ensembles or hybrid approaches are usually preferred.

If one is to make a prediction concerning the remaining useful life, it is necessary to do more than just classify. The maintenance planner must have an estimate of the rate at which degradation is progressing as well as an assessment of how uncertain that estimate is. Arguments advanced by physics-informed RUL methods state that it is possible to enhance plausibility and generalization by combining data-driven learning with reliability models, degradation laws, or physical constraints. The research carried out by Shao et al. on subsea valves is useful since it makes use of Bayesian and Weibull-based reasoning to quantify degradation in the case of small sample sizes. In safety-critical pressure-control applications, probabilistic RUL intervals are more defensible than a single deterministic date; in the case where a model predicts twenty days remaining with a wide uncertainty range the appropriate action would be to carry out an inspection immediately; but if the same mean prediction has a narrow interval and the consequences are low, maintenance could be scheduled for the next planned shutdown.

V. CRITICAL SYNTHESIS OF THE EVIDENCE

The literature shows that AI-assisted maintenance is most strongly supported in those cases in which the predictions are based on a measurable engineering relationship, choke studies being a suitable example. Machine learning can accurately relate the position of the choke, the pressure, the type of fluid, and the production variables to flow behaviour. This ability enables the use of a residual-based maintenance strategy, whereby a model is trained using data from periods when the system was known to be in good condition and degradation is then inferred from a systematic decline in performance. This approach is superior to having a black-box classifier learn to tell the difference between "eroded" and "healthy" states from a small number of inspection labels. It also allows process engineers to determine whether a change is consistent with erosion, deposition, or with changes in fluid conditions. Investigations into direct choke erosion show that exposure to sand and the physics of erosion can further limit the interpretation.

In contrast, valve prognostics involve sparse data and are safety-critical, with failure accumulation not being allowed during training. The DBN-KF method and the data-model-linked subsea valve approaches highlight the need for probabilistic reasoning and reliability models. The benefit of these methods is not that a particular subsea model can be directly transferred to a land wellhead, but rather that they enable a consistent integration of health indicators, uncertain parameters, prior engineering knowledge, and the rare condition measurements. This gives a more realistic foundation for prognosing master valves, wing valves, and surface safety valves than depending on a deep neural network which requires thousands of run-to-failure examples.

The insights gained from studies of pumping systems can be put to use in a variety of situations. When looking at the water-injection pump it becomes clear that the selection of algorithm, the preprocessing steps, feature selection, and optimization are all factors which influence the performance of predictive maintenance. With regard to the NGL pump, reliability modelling, the assessment of sensor condition, and the diagnostic logic are combined rather than relying on a single predictor. Research concerning electric submersible pumps (ESP) shows that it is possible to carry out multi-state classification using field SCADA systems, on the condition that the labels are linked to degradation trends, whereas more general reviews of ESP failures classify the mechanical, electrical, operational, and environmental causes into diagnostic pathways. The main idea is that maintenance intelligence is a system in which data quality, failure taxonomy, feature design, model validation, and decision rules all have to be developed together.

Digital twins may serve as the means of integration. As the 2020 review of digital twins in the oil and gas industry made clear, the main themes that were identified were asset integrity, lifecycle management, cybersecurity, standardization, and industrial implementation. A later maintenance case study illustrates how real-time data, simulation, machine learning, and reasoning can be combined within a digital-twin framework when it is used with an oil extraction pumping system. The 2025 systematic review of the digital-twin requirements for oil and gas production also emphasizes the importance of monitoring, optimization, failure prediction, what-if simulation, and safety support. With respect to wellhead equipment, a practical digital twin does not have to replicate all the mechanical details; it only needs to adequately represent the operating envelopes, the performance equations for the valves and chokes, the degradation states, sensor confidence, and the maintenance history in order to determine whether an AI prediction is physically credible.

The evidence base does have some important weaknesses. First, although a number of studies manage to improve predictive accuracy by using retrospective data, they do not demonstrate that this results in any actual benefit when it comes to maintenance in the future. Because accuracy, as measured by the F1 score, RMSE or R-squared, does not directly indicate the avoidance of failure, or the reduction in production delays, the decrease in false alarms, or improvements in safety, these figures are not relevant in this situation. Second, the datasets are usually tailored to a specific asset or field; a model created for one type of choke geometry, one fluid system, or one method of operation may not function when used in a different field. Third, the datasets that are made public tend to have cleaner labels than those from actual maintenance systems, since work orders can be delayed, the causes of failures are not always certain, and components can be changed whenever shutdowns occur. Fourth, the consequences of false negatives and false positives are not equal; it is far more serious to fail to detect a degrading pressure barrier than it is to carry out an unnecessary inspection, and for this reason threshold selection should be based on risk rather than being optimised solely for overall accuracy.

It is exactly due to these weaknesses that explainability and uncertainty have to be considered as design requirements; when an anomaly occurs it should be accompanied by the variables and temporal evidence which led to it; a diagnosis should indicate the plausible alternative causes; and an RUL estimate should include a measure of confidence or probability. Research into SCADA anomalies has shown that it is possible to incorporate interpretable dynamic limits and the ability to isolate the root cause into detection frameworks. Physics-informed prognostics provides a complementary way of avoiding unrealistic extrapolation. Together, these methods allow for a maintenance discussion in which AI serves to support rather than replace engineering judgment.

VI. DEPLOYMENT ARCHITECTURE FOR UPSTREAM OPERATIONS

The architecture for a field-ready system should start with the asset and end with a controlled maintenance decision. Figure 1 illustrates a flow that is focused on the asset, connecting the wellhead equipment to sensing and operational context, data-quality services, analytics, and the maintenance decision stage. The physical asset part includes the Christmas tree, the production choke, the surface safety valve or the emergency shutdown valve, the actuators, and the pressure instrumentation. The data layer combines the process variables with the valve commands, the positions, the alarms, and where available the indications of sand or solids, the inspection results, and the maintenance history. Context from well tests, startup events, choke changes, and planned interventions is maintained so that the analytics can tell the difference between changes in operations and degradation.

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DOI: https://doi.org/10.64388/IREV10I3-1722968

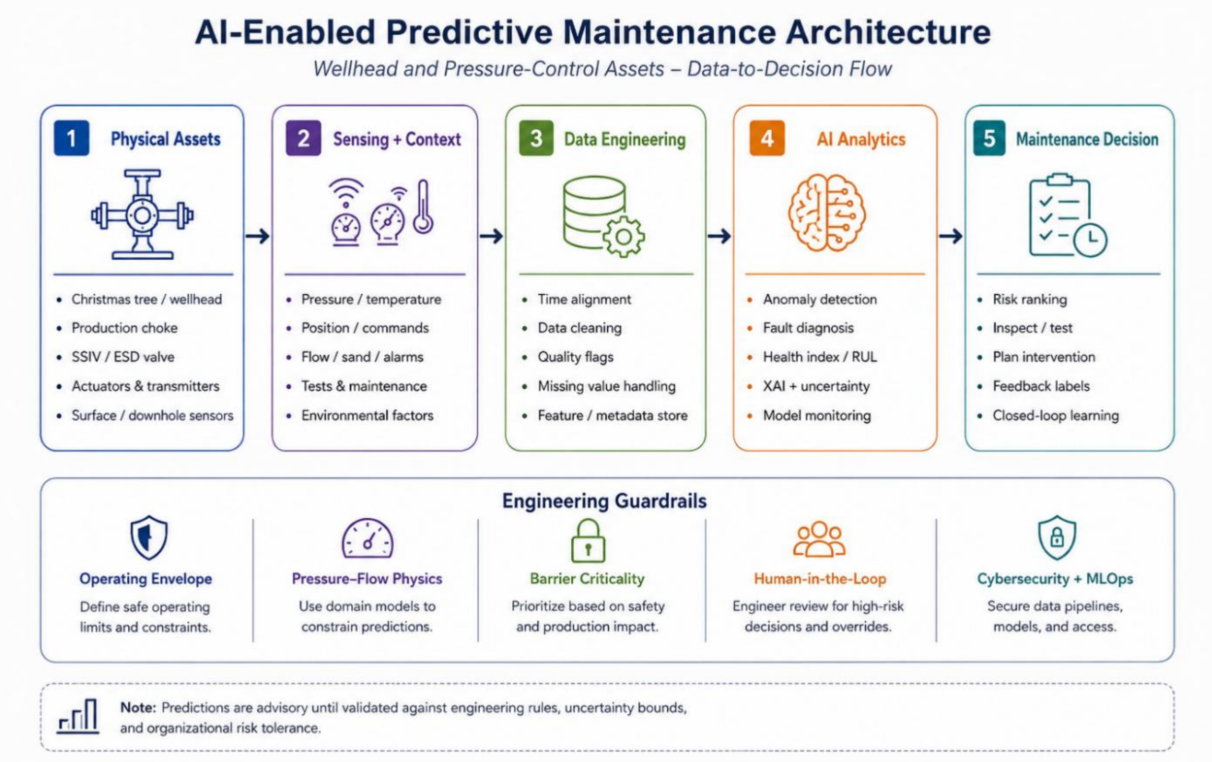

Figure 1. AI-enabled predictive maintenance architecture for wellhead and pressure-control assets.

Each of the different parts of the analytics system should be separate and individual. The model employed for identifying normal behaviour is capable of detecting any kind of deviation; the diagnostic component can rank the various possible causes of failure; the degradation model can estimate the health status and the remaining useful life (RUL) each time there is enough evidence; and the explanation layer has to report the key factors involved together with the degree of uncertainty. A summary of the appropriate model types is given in Table 2. Instead of depending on a single all-purpose model, operators could use a gradient-boosting model for classifying structural health, an interpretable anomaly detector for the continuously streamed SCADA tags, and a probabilistic RUL model for valves which have sparse inspection data; a digital twin or a lightweight physics model could then check for consistency with the pressure-flow and actuation constraints before any recommendations are made.

Table 2. Suitability of AI model families for wellhead predictive maintenance.

Model family	Data demand	Strengths for wellhead PdM	Limitations	Best-fit use
RF / XGBoost / CatBoost	Low-moderate; structured tags	Nonlinear interactions; robust baseline; feature importance; handles mixed features	Can overfit field-specific labels; temporal behavior requires engineered features	Health-state classification; residual correction; risk ranking
SVM / one-class methods	Low-moderate	Strong with small datasets; useful boundary models	Scaling/tuning sensitive; probability calibration may be weak	Small-sample diagnosis; novelty detection

Model family	Data demand	Strengths for wellhead PdM	Limitations	Best-fit use
Isolation Forest / probabilistic anomaly models	Mostly healthy data	Works without many failure labels; continuous screening	Anomaly ≠ failure; sensitive to operating-mode mixing	Early warning and triage
LSTM / TCN / Transformer	High-frequency sequences; larger histories	Learns temporal degradation and multivariate dynamics	Data hungry; less transparent; computationally heavier	Actuator signatures; dense pressure/acoustic/vibration histories
Bayesian / Weibull / state-space degradation	Small-intermittent data plus priors	Represents uncertainty; supports probabilistic RUL	Requires defensible degradation assumptions	Safety-critical valves; inspection-driven prognostics
Physics-informed / digital-twin hybrid	Data plus engineering model	Physical plausibility; scenario testing; better extrapolation potential	Integration and calibration effort; model governance	Choke performance drift; barrier decision support

The decision layer converts the predictions into risk. In order to be of use, a risk score has to consider the probability of degradation, the predicted time to functional failure, the degree of uncertainty, the level of safety criticality, the effects on production, the presence of redundancy, the ease with which the component can be inspected, and the next maintenance opportunity. Consequence of this is that different actions can be taken in response to the same anomaly score depending on the asset in question. For instance, a non-critical choke with stable containment and a redundant production route could be dealt with by means of a planned inspection, whereas indications of leakage or of impaired isolation in a main safety barrier would require immediate testing or a shutdown. Therefore, the output from the AI acts as one input to a risk-based maintenance process rather than causing the automatic generation of a work order.

When one is deciding between using edge and cloud computing, account should be taken of the latency involved and the quality of the connection. If it is necessary to carry out anomaly detection quickly—for example, in emergency situations or for near-real-time operational responses—then this detection should be carried out close to the control system; on the other hand, computationally intensive tasks such as model training and fleet analytics can make use of the central infrastructure. As has already been stated in the literature concerning IoT in the oil and gas industry, both the advantages of connected sensing and the problems associated with communications, cybersecurity, and technology readiness in hazardous environments have been identified [1]. Similarly, research into digital twins shows that standardization and information security are constraints with regard to deployment . Operational technology models must therefore be set as read-only by default at the start of deployment, together with strict version control, access management, audit trails, and independent safety logic. Preventive maintenance must never undermine the existing protective measures.

It is just as crucial to manage the entire lifecycle of a model. As reservoir pressure decreases, changes take place in the composition of the fluids, the water cut increases, the equipment is replaced, and the operating strategies are altered, thereby causing the production conditions to change. A model that was accurate when it was first put into use may eventually become improperly calibrated. Monitoring should therefore focus on the completeness of the data, the distributions of the features, the rates of irregularities, the level of prediction confidence, and the results after maintenance. Figure 2 illustrates a closed loop which involves observing, detecting, diagnosing, prognosing, deciding, acting, and learning. Following an inspection or a maintenance operation, the verified findings are returned in order to improve the labels and to recalculate the model. This feedback transforms maintenance events from simple

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DOI: https://doi.org/10.64388/IREV10I3-1722968

individual records into evidence that enhances future predictions.

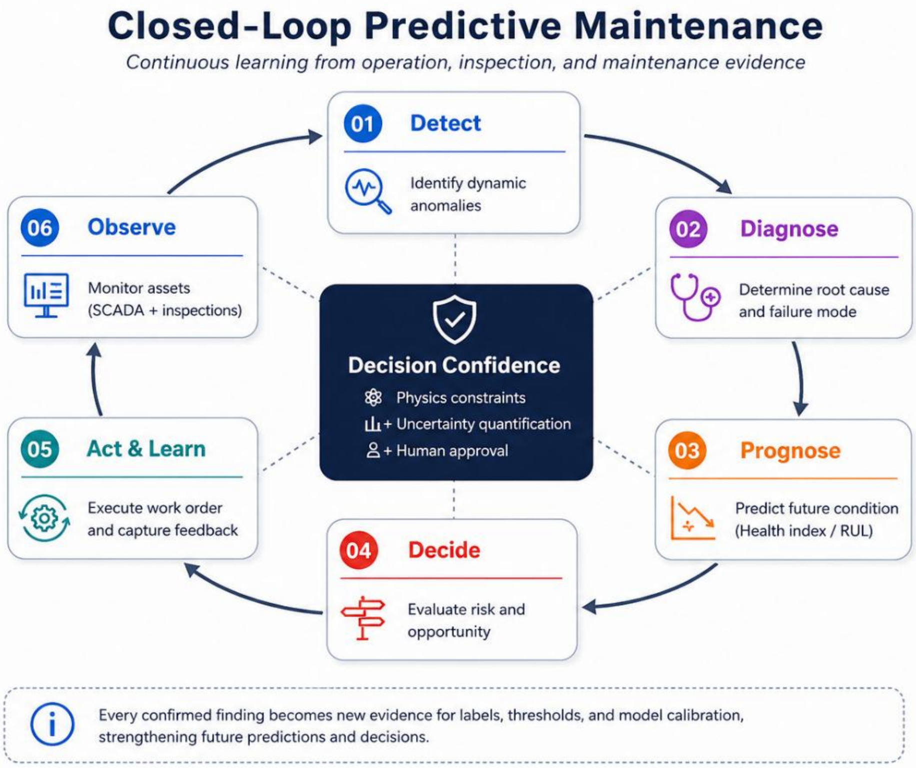

Figure 2. Closed-loop predictive maintenance cycle.

VII. CHALLENGES AND RESEARCH GAPS

The key statistical issue is the frequency of rare failure events. Because safety-critical wellhead equipment is designed, checked and maintained in good condition with the objective of preventing run-to-failure scenarios, the most important kinds of failure are generally those that are represented the least. Consequently, conventional supervised learning may seem to achieve a high level of accuracy by merely predicting the normal case. Research in this field should take into account class-specific recall, precision, the number of false alarms per operating hour, and detection lead time. Experience obtained from field work on electric submersible pumps illustrates just how severe the imbalance can be and how valuable it is to use domain-informed transitional labels. For wellhead valves, a label showing incipient degradation, derived from slower travel, leakage-test trends or pressure residuals, is more useful than a simple failed/not-failed label.

There is another gap when it comes to generalization. Differences occur in respect to the choke geometry, the material used, the pressure rating, the type of actuator, the quality of the instrumentation, the composition of the fluid, sand production, and the local control methods. In order to be used across different wells, fields, and types of equipment, models have to be externally validated. Even though transfer learning and domain adaptation may reduce the quantity of newly labelled data that is required, these techniques must still ensure that physical meaning is preserved. The general AI literature warns that petroleum models are often still difficult to transfer because of the field-specific character of the datasets and operating conditions, and it follows that a credible study should therefore maintain the random train-test splitting separate from any actual cross-well or cross-field validation.

Ground truth is also an issue. The fact that a maintenance record shows a choke has been replaced does not prove that erosion has taken place; the replacement might have been preventive, opportunistic, or have been caused by a problem with the actuator. High-quality research into predictive maintenance calls for a failure taxonomy that is connected to evidence from inspections, teardowns, leak tests, calibration records, and work-order codes. Research into the integrity of offshore pipelines likewise emphasizes the importance of combining AI with the existing asset-integrity procedures rather than viewing the analytics as a simple replacement.

The same principle applies at the wellhead: the model should learn from verified integrity evidence whenever possible.

In the end, there are no currently accepted economic and safety standards by which to judge the models. A model that can detect degradation two days earlier may be useful in the case of a well with a high production rate, but would be of no relevance when maintenance cannot be carried out before a planned shutdown. Future trials should, together with the technical metrics, also take into account the amount of deferment avoided, the reduction in unplanned shutdowns, inspection efficiency, spare parts planning, the number of false call-outs, and the degree of risk reduction. Only in this way would AI research be brought in line with the actual objective of maintenance—which is to maintain safe and reliable production at a lifecycle cost that is acceptable.

VIII. FUTURE RESEARCH AGENDA

Future research should focus on hybrid models which incorporate the pressure-flow relationships, the physics of valve actuation, the reliability structure, or the degradation constraints while still maintaining the flexibility of machine learning. Research into physics-informed remaining useful life provides a methodological basis for combining learned representations with physical consistency. In the case of chokes, models based on normal flow can be combined with those relating to erosion or deposition; for valves, Bayesian or reliability models can integrate inspection data with the intermittent monitoring; and for transmitters, redundancy and the mass-balance relationships can be used to constrain drift detection. Hybrid approaches are likely to enhance the ability to make predictions beyond the specific conditions present in the training data.

A further promising method is self-supervised learning because, although failures are rare, there is a great deal of normal SCADA data available. Models can learn representations from unlabelled sequences and then refine themselves in response to small labelled datasets containing failures. The approach should include uncertainty-aware learning so that the system is able to identify when a new operating condition lies outside the range of its experience. As is shown in general reviews of remaining useful life, the various stages involved in data acquisition, health-index construction, prediction and maintenance decision-making should be linked together rather than concentrating only on optimising the final algorithm. With regard to wellhead assets, the research should evaluate the entire process from sensor reliability right the way through to actionability.

IX. CONCLUSION

The use of AI to enable predictive maintenance can considerably improve the way in which wellhead and pressure-control equipment is managed, on the condition that the algorithms are included in an engineering system one which considers the asset's function, the operating context, the quality of the data, and uncertainty. There is now evidence to indicate that the behaviour of wellhead chokes can be accurately learned from field variables, that erosion and degradation can be represented by data-driven models, and that it is possible to estimate a probabilistic remaining useful life even when valve history data is sparse, provided that the data is combined with reliability knowledge. Studies concerning petroleum pumps and equipment also demonstrate the practicality of ensemble learning, time-aware features, domain-informed labels, and integrated maintenance logic.

A layered method is therefore preferable to one which relies on algorithms. Reliable sensing combined with context-aware preprocessing results in a trustworthy database; interpretable anomaly detection identifies any departures from normal behaviour; diagnosis associates these departures with possible failure mechanisms; probabilistic prognosis evaluates the degree of degradation and the remaining life; and a decision-making layer which is based on risk determines whether to monitor, inspect, test, derate or intervene. Digital twins are able to connect the various layers and provide a continuous feedback mechanism between the physical assets and the analytical models. The key research need is no longer simply achieving higher accuracy when working offline but rather demonstrating and ensuring transferable value in the field: earlier and more reliable warnings, fewer unnecessary interventions, less production delay, clearer prioritisation of maintenance, and greater assurance that the pressure-control barriers are still suitable for their purpose.

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