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Advances in Predictive Maintenance of Industrial Boilers Using Condition Monitoring and Thermal Efficiency Analytics

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Abstract
Industrial boilers are capital-intensive assets whose unplanned outages carry severe consequences for production continuity, energy cost, and personnel safety. Traditional maintenance regimes, based either on running equipment to failure or on fixed calendar intervals, are increasingly unable to balance reliability against cost in modern process industries. This paper reviews recent advances, up to 2022, in predictive maintenance of industrial boilers achieved through the integration of condition monitoring technologies and thermal efficiency analytics. It examines the principal sensing modalities applied to boiler systems, including vibration analysis, infrared thermography, ultrasonic thickness measurement, acoustic emission, flue gas analysis, online water chemistry monitoring, and emerging aerial and geospatial inspection methods, and discusses how efficiency indicators derived from heat loss accounting expose degradation mechanisms such as fouling, slagging, scaling, and heat exchanger deterioration before they manifest as failures. The paper then surveys data-driven frameworks, including machine learning classifiers, statistical prognostic models for remaining useful life estimation, and digital twin architectures, that convert monitored data into actionable maintenance decisions. Because predictive maintenance programs succeed or fail within a wider organizational system, the review also draws on the adjacent literatures of data infrastructure and governance, cybersecurity of operational technology, occupational safety management, maintenance supply chain and spare parts logistics, economic evaluation and decision support, and the energy transition context in which boiler assets now operate. Reported industrial outcomes indicate meaningful reductions in unplanned downtime and fuel consumption, alongside improved inspection targeting. Persistent challenges include sensor reliability in harsh combustion environments, scarcity of labeled failure data, integration with legacy control systems, and organizational readiness.

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1. Introduction

Steam generation remains a foundational utility across power generation, petrochemicals, pulp and paper, food processing, and district heating. Industrial boilers operate continuously under high pressures and temperatures, in the presence of aggressive combustion products and demanding water chemistry, and their failure modes range from gradual efficiency erosion to catastrophic tube ruptures. Studies of forced outages in thermal plants consistently identify boiler tube failures as the single largest contributor to lost availability, and the economic penalty of a single unplanned boiler outage in a large process facility can reach hundreds of thousands of dollars per day when lost production is included.

Historically, boiler maintenance has followed two paradigms. Corrective maintenance repairs equipment after failure, accepting downtime as an unavoidable cost. Preventive maintenance schedules interventions at fixed intervals, which reduces catastrophic failures but frequently results in unnecessary work, intrusive inspections that themselves introduce defects, and residual failures between intervals. Predictive maintenance, sometimes termed condition-based maintenance, represents a third paradigm in which the actual health of the asset, inferred from measured data, dictates when and where intervention occurs (Mobley, 2002). The transition from reactive to predictive maintenance philosophies has been documented across mechanical systems generally (Sunday *et al*., 2020), and boilers are among the assets for which the case is strongest.

Two technological currents have converged in the past decade to make predictive maintenance practical for boiler systems. The first is the maturation and cost reduction of condition monitoring instrumentation, including permanently installed wireless sensors capable of surviving boiler house environments. The second is the growth of analytics capability, from classical statistical process monitoring to machine learning and digital twin modeling, enabled by inexpensive computation and industrial data infrastructure associated with Industry 4.0 (Zonta *et al*., 2020). A distinctive feature of the boiler domain is that thermal performance data, routinely collected for energy accounting, doubles as a rich diagnostic signal: many degradation mechanisms announce themselves first as efficiency losses.

In terms of method and scope, this paper is a narrative review covering literature published up to and including 2022. Sources were drawn from the core condition monitoring, prognostics, and boiler engineering literature, from international standards, and from a consolidated body of related and semi-related applied research spanning predictive analytics, occupational safety, cybersecurity and data governance, supply chain management, enterprise decision analytics, and energy systems. The deliberate breadth reflects a central argument of the review: the effectiveness of a boiler predictive maintenance program is determined jointly by its sensing and modeling core and by the surrounding organizational systems, so a review confined to sensors and algorithms would misrepresent the determinants of success observed in practice. Semi-related sources were included where the methods, architectures, or governance lessons they report transfer recognizably to boiler maintenance, and the text states the nature of the transfer in each case rather than leaving the connection implicit.

Some terminological ground rules are useful. Condition monitoring refers to the acquisition and interpretation of data that indicates equipment health. Condition-based maintenance uses that information to trigger maintenance actions. Predictive maintenance adds a forecasting element, estimating when a limit will be reached, and prescriptive maintenance goes further by recommending the specific action to take among alternatives. In industrial usage these terms overlap heavily, and this review uses predictive maintenance as the umbrella term. Two limitations of the review should be acknowledged at the outset. First, as a narrative rather than systematic review, it does not claim exhaustive coverage or formal quality scoring of the included studies. Second, much of the quantitative benefit evidence in this field originates from vendors and implementers rather than independent evaluations, a bias discussed further in Sections 6 and 7. Within these limits, the review aims to give practitioners and researchers an integrated map of the field as it stood in 2022.

This review deliberately takes a broad view of the predictive maintenance ecosystem. Alongside the core sensing and analytics literature, it draws on related and semi-related work in adjacent domains where methods and organizational lessons transfer directly to boiler practice: predictive analytics developed in logistics, finance, and operations; safety management and risk governance in high-hazard industries; cybersecurity and data governance for the digital infrastructure on which monitoring depends; procurement and spare parts logistics that determine whether predictions can be acted upon; and the energy transition context that reshapes the economics of thermal assets. The remainder of the paper follows a conventional research paper structure: Section 2 summarizes degradation mechanisms, Section 3 reviews condition monitoring and thermal efficiency analytics, Section 4 surveys data-driven predictive frameworks together with the digital infrastructure and security they require, Section 5 treats the organizational, logistical, economic, regulatory, and sustainability context, Section 6 presents application scenarios and reported outcomes, Section 7 discusses the findings, Section 8 sets out challenges and future directions, and Section 9 concludes. The contribution of the paper is not a claim of algorithmic novelty but a novel integrative synthesis: it is, to the authors' knowledge, among the first reviews to connect the sensing and analytics core of boiler predictive maintenance explicitly to the adjacent bodies of work on data governance, operational technology security, safety science, maintenance supply chains, enterprise decision analytics, and the energy transition, and to argue from that synthesis that predictive maintenance capability is a system property of the owning organization.

2. Boiler Degradation Mechanisms and the Maintenance Context

Effective predictive maintenance begins with an understanding of the physical mechanisms that drive boiler deterioration, because every monitoring technique and every analytic indicator is ultimately a proxy for one or more of these mechanisms (Kitto and Stultz, 2005). This section reviews them by location and physics, and then restates the maintenance decision problem they jointly create.

2.1. Fireside Mechanisms

On the fireside, the dominant mechanisms are deposition and material loss. Slagging refers to molten or partially fused ash deposits on radiant furnace surfaces, while fouling denotes the sintered or loosely bonded deposits that accumulate on convective surfaces downstream; the distinction matters because the two respond to different cleaning methods and produce different thermal signatures. Deposit behavior is governed by ash chemistry, particularly the proportions of alkali metals, sulfur, chlorine, iron, and calcium, and by local gas temperature relative to the ash fusion characteristics of the fuel. Fuel switching and fuel blending, increasingly common as plants pursue cost and emissions objectives, can therefore change the fouling regime of a boiler that had operated predictably for decades, and this is one of the strongest arguments for continuous rather than periodic performance monitoring.

Material loss on the fireside proceeds through high-temperature corrosion and erosion. High-temperature corrosion mechanisms include sulfidation under reducing conditions near burners, molten alkali sulfate attack beneath deposits, and chlorine-accelerated attack when high-chlorine fuels such as certain biomass and waste streams are fired. Fly ash erosion thins tubes preferentially at flow concentration points such as gas lanes, baffle edges, and soot blower paths, and erosion by the soot blowing medium itself is a recognized self-inflicted mechanism when blowing is excessive or poorly aimed. These mechanisms connect directly to the corrosion management literature (Atta *et al*., 2018; Atta *et al*., 2020): inhibitor selection, coating strategy, and inspection targeting all depend on correctly identifying which fireside mechanism is active, a diagnosis that deposit sampling and localized thickness trending can resolve.

2.2. Waterside Mechanisms

Waterside degradation is fundamentally a water chemistry problem. Scaling from hardness salts and silica deposits an insulating layer on the inner tube wall, raising tube metal temperature for a given heat flux and setting the stage for overheating failures; a fraction of a millimeter of scale can raise metal temperature by tens of degrees. Oxygen pitting occurs where dissolved oxygen is inadequately removed or where shutdown lay-up practice admits air to wet surfaces. Under-deposit corrosion mechanisms, including caustic gouging and acid phosphate corrosion, concentrate aggressive species beneath porous deposits in high heat flux regions. Hydrogen damage embrittles steel beneath deposits under acidic excursions, producing thick-lip ruptures with little warning. Flow-accelerated corrosion thins carbon steel in single-phase and two-phase flow regions of economizers and feedwater systems, with rate maxima at intermediate temperatures and specific chemistry conditions.

Each of these mechanisms leaves a chemical fingerprint before it leaves a mechanical one, which is why Section 3 treats online chemistry monitoring as a first-class condition monitoring technique rather than a utility function. Cycle chemistry excursions, their duration and depth, can be logged and accumulated into exposure indices per circuit, and plants that maintain such indices are able to prioritize waterside inspection scope with far greater precision than plants that inspect uniformly. The practice parallels the exposure-based risk accumulation used in the safety literature reviewed in Section 5.1, where leading indicators are tracked long before harm occurs.

2.3. Mechanical, Creep, and Fatigue Mechanisms

Mechanical damage accumulates through creep, fatigue, and their interaction. Superheater and reheater elements operate in the creep range, where life is consumed as a nonlinear function of metal temperature and stress; sustained operation even 10 to 20 degrees Celsius above design can consume creep life several times faster than intended, which is why tube metal thermocouples and virtual temperature sensing carry such diagnostic value. Fatigue arises from start-stop cycling, load ramping, and attemperator spray events, and it concentrates at thick-section components such as headers and drums where thermal gradients generate cyclic stress. Dissimilar metal welds between ferritic and austenitic sections are recognized weak points with their own failure statistics. As flexible operation becomes the norm for thermal plants in renewable-heavy grids, a theme developed in Section 5.4, cycling-driven mechanisms are claiming a growing share of failures, shifting monitoring priorities from steady-state indicators toward transient event counting, ramp rate tracking, and stress estimation from measured temperature differentials.

2.4. Refractory, Casing, Structures, and Auxiliaries

Beyond the pressure envelope, refractory linings crack and spall under thermal cycling, insulation systems degrade and admit casing corrosion beneath lagging, expansion joints and casings develop air ingress paths that corrupt combustion control and dilute efficiency, and structural steel and supports corrode in the humid, sulfur-bearing environment of the boiler house. Auxiliary machinery, including fans, pumps, mills, and soot blower drives, accumulates the conventional bearing, alignment, and wear degradation of rotating equipment. None of these mechanisms individually rivals a tube rupture for drama, but collectively they account for a large share of efficiency loss, derating, and maintenance spending, and they are among the most economically attractive monitoring targets because the required instrumentation is inexpensive and mature.

2.5. The Maintenance Decision Problem

These mechanisms differ widely in their time constants, from creep damage accumulating over decades to a tube leak that escalates within days, and in their observability. This heterogeneity is precisely why a portfolio of monitoring techniques, rather than any single sensor, is required. The maintenance decision problem is to detect incipient degradation, diagnose its cause and location, prognosticate its progression, and schedule intervention at the point that minimizes total cost and risk. Jardine, Lin, and Banjevic (2006) formalized this detect-diagnose-prognose pipeline for condition-based maintenance generally, and it maps naturally onto boiler practice: for example, a rising flue gas exit temperature (detection) may be attributed to convective pass fouling (diagnosis), its trajectory extrapolated against a cleanliness threshold (prognosis), and a soot blowing campaign or an outage cleaning scheduled accordingly (decision).

3. Condition Monitoring and Thermal Efficiency Analytics

Condition monitoring of boilers spans the pressure parts, the combustion system, the water-steam circuit, and the balance of plant. Table 1 summarizes the principal techniques and the failure modes they address.

Table 1: Principal condition monitoring techniques applied to industrial boilers.

Technique	Measured Parameters	Typical Failure Modes Addressed
Vibration analysis	Velocity, acceleration, spectral signatures	Fan and pump bearing wear, misalignment, imbalance in draft equipment
Infrared thermography	Surface temperature distribution	Refractory degradation, insulation loss, localized tube overheating
Ultrasonic thickness testing	Wall thickness of tubes and drums	Erosion, corrosion, and flow-accelerated corrosion of pressure parts
Acoustic emission monitoring	High-frequency stress waves, leak noise	Early tube leak detection, crack propagation in headers
Flue gas analysis	O_2, CO, CO_2, NO_x, exit gas temperature	Combustion inefficiency, air ingress, burner degradation
Water chemistry monitoring	pH, conductivity, dissolved oxygen, silica	Internal corrosion, scaling, carryover, under-deposit attack

3.1. Pressure Part Integrity Monitoring

Ultrasonic thickness testing remains the workhorse for tracking erosion and corrosion of tubes, headers, and drums, and recent advances have shifted it from periodic manual surveys toward permanently installed high-temperature transducers that stream thickness data continuously. Weld integrity deserves particular attention in boilers, whose pressure parts are joined by thousands of welds subject to fatigue and creep; advances in non-destructive testing methods for weld integrity evaluation in high-capacity power infrastructure (Atta *et al*., 2021) and in welding inspection standards and quality assurance practice for large projects (Atta *et al*., 2022) directly strengthen the inspection basis for pressure part life management. Acoustic emission and acoustic leak detection systems, using arrays of waveguide-mounted sensors on furnace walls, detect the characteristic broadband noise of steam escaping from a pinhole leak, often days before the leak becomes visible in makeup water balances. Early leak detection is among the highest-value monitoring applications because a small primary leak, if run on, commonly cuts adjacent tubes and multiplies repair scope.

3.2. Thermal and Combustion Monitoring

Infrared thermography, both handheld and fixed, maps casing and refractory temperatures and identifies insulation failures and hot spots associated with internal deposit patterns. In-furnace imaging and tube metal thermocouples on superheaters provide direct evidence of overheating that precedes creep and short-term overheat failures. On the combustion side, continuous flue gas analysis of oxygen, carbon monoxide, and exit gas temperature characterizes burner condition, air ingress through casing leaks, and excess air control quality. Departures of the O_2 to CO relationship from the commissioning baseline are a sensitive indicator of burner wear or damper faults.

3.3. Water-steam cycle chemistry monitoring

Online analyzers for pH, cation conductivity, dissolved oxygen, sodium, and silica have become standard in larger plants, and their trend data is diagnostic rather than merely protective. Sustained chemistry excursions correlate strongly with subsequent waterside failure mechanisms, so chemistry histories are increasingly incorporated as covariates in tube life models. Steam purity monitoring similarly protects downstream superheaters and turbines from carryover deposition.

3.4. Rotating Auxiliaries and Electromechanical Equipment

Draft fans, feedwater pumps, mills, and soot blower drives are monitored with conventional vibration and motor current signature analysis. Because most boiler auxiliaries are motor driven, the modeling of electrical machine losses and performance provides a complementary diagnostic channel: multi-algorithm optimization studies of loss and weight objective functions in induction motors (Amayo, 2017; Amayo & Popoola, 2017a; Amayo *et al*., 2015) illustrate the model-based baselines against which in-service motor efficiency deviations can be judged, while work on voltage control in networks with distributed generation (Oshevire *et al*., 2017) is relevant to the power quality conditions under which plant motors operate. Fault detection concepts proven in adjacent thermal equipment transfer readily; sensor-based smart fault detection developed for HVAC systems (Sunday & Omoegun, 2022) employs the same residual-based logic applied to boiler fans and pumps. More broadly, structured performance evaluation and factor analysis methodologies developed for process machinery (Bello, Adama, *et al*., 2022; Bello, Tawose, *et al*., 2022) inform how auxiliary equipment health indices are constructed and validated. Wireless triaxial accelerometers with on-sensor spectral processing have substantially reduced the cost of covering these assets.

3.5. Aerial, Geospatial, and Remote Inspection Methods

A notable recent development is the extension of inspection beyond fixed instrumentation to aerial and geospatial platforms. Unmanned aerial vehicles carrying visual, thermal, and LiDAR payloads, originally reviewed and framed for electrical transmission line and power grid inspection programs (Dagodzo, 2018a; Dagodzo, 2018b), are now applied inside and around boiler houses: confined-space drones inspect furnace interiors, penthouses, and stacks without scaffolding, and external flights map stack condition and pipe rack corrosion. The supporting literature on pipeline and infrastructure corridor monitoring (Dagodzo & Ahiaeke Patrick, 2020), on integrated UAV, LiDAR, and geographic information system frameworks for corridor management (Dagodzo & Ahiaeke Patrick, 2021b), and on GIS applications in utility asset management (Dagodzo & Ahiaeke Patrick, 2021a) provides the data management patterns for georeferencing inspection findings to asset registers. Related advances in encroachment detection with geospatial methods (Dagodzo & Ahiaeke Patrick, 2022) and in deep learning classification of imagery for corridor management (Dagodzo *et al*., 2022) demonstrate the automated defect recognition pipelines that are now being retargeted at boiler casing, insulation, and structural steel imagery.

3.6. Sensor Technologies, Wireless Networks, and Data Acquisition Reliability

The credibility of every downstream analytic rests on the physical measurement layer, and this layer deserves explicit engineering attention. High-temperature service pushes sensors toward specialized designs: type K and type N thermocouples with appropriate sheathing for gas path and metal temperatures, high-temperature ultrasonic transducers with delay lines or waveguides for permanently installed thickness measurement, sapphire and specialty optical windows for in-furnace imaging, and purged or water-cooled housings for cameras and gas analyzers. Every one of these devices drifts, fouls, or fails in ways that mimic process degradation, so sensor validation must be designed into the system rather than assumed. Practical techniques include redundancy with cross-checking among related measurements, physical consistency checks derived from mass and energy balances, reference measurements taken during outages to re-anchor drifting instruments, and explicit sensor health indices reported alongside asset health indices so that users can distinguish a sick boiler from a sick sensor.

Wireless sensing has been the single biggest enabler of broader instrument coverage because it removes the cabling cost that historically confined monitoring to a few critical points. Industrial wireless protocols in the process sector, mesh-networked field instruments, and battery or energy-harvesting powered vibration nodes now permit dozens of measurement points to be added to an existing boiler at a small fraction of wired cost. The engineering considerations are network reliability in a metal-dense, high-temperature environment, battery life management, and coexistence with plant radio systems, and the network quality literature (Amayo & Popoola, 2017b) is relevant to planning this layer.

Data acquisition reliability also has a procedural dimension: calibration schedules, management of instrument configuration, and documentation of every sensor relocation or replacement are prerequisites for trustworthy long-horizon trends, since an undocumented transducer swap can masquerade as a step change in asset condition and corrupt years of baseline.

3.7. Thermal Efficiency Analytics as A Diagnostic Instrument

Boiler efficiency is conventionally evaluated by the input-output (direct) method or by the heat loss (indirect) method codified in ASME PTC 4 (ASME, 2013). The indirect method is the more diagnostic of the two because it decomposes inefficiency into attributable loss streams: dry flue gas loss, losses due to moisture in fuel and from hydrogen combustion, unburned carbon loss, radiation and convection loss, and blowdown loss. Each loss stream is coupled to specific degradation mechanisms, which allows efficiency accounting to function as a continuous condition monitor for the heat transfer surfaces and combustion system. The same coupling of thermodynamic efficiency accounting to control strategy has been demonstrated in other thermal systems, including air conditioning plant (Sunday *et al*., 2019), underscoring that efficiency analytics is a general diagnostic paradigm for heat machinery.

Several analytic indicators have proven especially useful in practice. First, the flue gas exit temperature, corrected for load and ambient conditions, trends upward as convective surfaces foul and as economizer or air heater performance degrades; a sustained rise of 20 degrees Celsius corresponds to roughly a one percent efficiency penalty in typical designs. Second, heat transfer cleanliness factors, computed section by section as the ratio of observed to expected heat absorption, localize fouling to the furnace, superheater, economizer, or air heater rather than merely signaling that fouling exists somewhere. Third, excess air and unburned carbon trends expose burner and mill degradation. Fourth, an increasing gap between feedwater flow and steam flow, corrected for blowdown, points to leakage.

A significant advance of the past decade is the shift of these calculations from periodic performance tests to continuous online computation using plant historian data, with expected-value baselines generated by regression or neural network models trained on clean-condition operation across the load range. This transforms efficiency analytics from an energy reporting function into a real-time anomaly detector. Closed-loop applications have followed, most prominently intelligent soot blowing, in which cleanliness factors drive the selective activation of soot blowers so that cleaning effort is directed where deposits actually are, reducing both steam consumption for blowing and the tube erosion caused by unnecessary blowing. The design of such closed loops benefits from the wider literature on adaptive control models for AI-driven automation in regulated operational settings (Sanni, Iwuanyanwu, *et al*., 2022), which addresses how automated actions are constrained, supervised, and audited. The economic logic is compelling: efficiency analytics pays for itself in fuel even before its maintenance value is counted, since a one percent efficiency gain in a continuously operated 100 tonne per hour boiler represents a substantial annual fuel saving as well as a proportional reduction in carbon dioxide emissions.

Method selection and uncertainty deserve comment. The direct method requires accurate fuel flow and heating value measurement, which is straightforward for gas but difficult for coal, biomass, and multi-fuel firing, where fuel sampling and analysis uncertainty can exceed the efficiency changes being sought. The indirect method is more robust to fuel metering error because most loss terms are computed from flue gas composition and temperatures, but it depends on representative gas sampling and on assumptions for minor losses. In continuous online implementations, the practical resolution is to compute both where possible, monitor their divergence as a data quality indicator, and place confidence intervals on the efficiency estimate by propagating instrument uncertainties through the loss calculations. Reporting efficiency without its uncertainty invites false alarms on noise and, worse, false confidence in favorable numbers.

Normalization is the second methodological pillar. Raw efficiency varies with load, ambient temperature, fuel moisture, and excess air setpoint for entirely legitimate operational reasons, and a monitoring system that ignores this will bury genuine degradation signals under operational variation. Effective systems therefore compare measured performance against a condition-dependent expected value, generated either from correction curves in the tradition of performance test codes or from empirical baseline models trained on known-clean operation across the full operating envelope. The residual between measured and expected performance, rather than the raw value, is the quantity that carries diagnostic content, and its statistical behavior under normal conditions defines the alarm thresholds that balance sensitivity against false alarm rate. This residual-based formulation is exactly the structure that the machine learning methods of Section 4 industrialize.

4. Data-Driven Predictive Frameworks and Digital Infrastructure

Condition monitoring and efficiency analytics generate large, heterogeneous data streams; predictive maintenance requires converting these into detections, diagnoses, and prognoses. Reviews of the machine learning literature for predictive maintenance (Carvalho *et al.*, 2019; Zonta *et al.*, 2020) identify several families of methods that have been applied to boiler problems.

4.1. Anomaly Detection and Fault Classification

Where labeled fault histories exist, supervised classifiers, including random forests, gradient boosted trees, support vector machines, and increasingly deep neural networks, have been trained to recognize precursors of tube leaks, fan faults, and combustion anomalies from multivariate sensor data. Multiple classifier architectures that balance detection sensitivity against false alarm cost have proven practical in industrial settings (Susto *et al*., 2015). Because labeled boiler failure data is scarce, unsupervised and semi-supervised approaches dominate in practice: principal component analysis based statistical process monitoring, autoencoder reconstruction error, and one-class classifiers learn a model of normal operation and flag departures from it. Auto-associative models of the boiler heat balance are particularly effective because they embed physical redundancy among temperatures, flows, and pressures. Instructive methodological parallels come from anomaly detection in other high-stakes domains: reviews of predictive analytics for anti-money laundering surveillance (Atakpa, 2021) and of machine learning advances in financial fraud detection (Atakpa & Abetoh, 2022) confront the same rare-event, high false alarm cost problem that boiler leak detection faces, and their treatment of alert triage and model drift transfers directly. Within the energy sector itself, interpretable machine learning for early failure prediction in distributed renewable assets (Komi & Adamolekun, 2021) demonstrates the explainability techniques that maintenance engineers increasingly demand of boiler models.

4.2. Prognostics and Remaining Useful Life Estimation

Prognostics extends detection into the time domain by estimating remaining useful life (RUL). Statistical data-driven approaches, surveyed comprehensively by Si *et al*. (2011), include regression-based trend extrapolation, Wiener and gamma stochastic degradation processes, and hidden Markov models. In the boiler context these have been applied to tube wall thinning trajectories from repeated ultrasonic surveys, creep life consumption of superheater elements computed from tube metal temperature histories, and fouling accumulation rates. Prognostic and health management design principles developed for rotary machinery (Lee *et al*., 2014) transfer directly to boiler auxiliaries. Degradation-centered lifecycle studies of other energy assets, such as grid-connected battery storage operating in harsh environments (Komi & Ganiu, 2022), reinforce the general lesson that degradation modeling and lifecycle economics must be treated jointly. RUL estimates with quantified uncertainty are the essential input to maintenance scheduling, since they allow interventions to be aligned with planned production stops.

4.3. Digital Twins and Hybrid Models

Digital twin architectures, in which a continuously updated virtual model of the boiler runs in parallel with the physical asset (Tao *et al*., 2019), represent the most integrative framework to emerge in recent years. For boilers, the twin typically couples a first-principles thermodynamic and heat transfer model with data-driven correction terms identified from operating data. The twin serves three maintenance functions: it supplies the expected values against which anomalies are detected, it enables what-if simulation of degradation scenarios and cleaning interventions, and it provides virtual sensing of quantities that cannot be measured directly, such as local tube metal temperatures in the furnace. Hybrid physics-informed models are especially valuable in this domain because purely data-driven models extrapolate poorly to the rare, off-design conditions under which failures often occur. Equally important is the human role in these systems; the state of the art in human-in-the-loop machine learning (Ladapo, Dosunmu, *et al*., 2022) describes how expert feedback is captured to label alerts, correct models, and maintain trust, all of which are essential in maintenance deployments.

4.4. Methods Transfer from Adjacent Predictive Analytics Domains

Boiler analytics has borrowed heavily, and productively, from predictive analytics developed in operations, logistics, and commerce, and a semi-related literature therefore merits citation in any complete account of the field. Demand forecasting with machine learning for revenue projection (Tonoyan *et al*., 2021a) and predictive cash flow modeling with advanced forecasting methods (Tonoyan *et al*., 2021b) supply the time series machinery, including gradient boosting and recurrent architectures, that is reapplied to steam demand and fuel consumption forecasting for load-aware maintenance planning. Simulation-based algorithmic process optimization and cost reduction studies (Tonoyan *et al*., 2022b) and conceptual models for machine learning driven predictive cost optimization (Tonoyan *et al*., 2022c) parallel the optimization of cleaning and outage schedules. Geospatial predictive analytics for facility siting and market analysis (Tonoyan *et al*., 2022a) mirrors the spatial analytics used to prioritize inspection across large multi-boiler sites. In supply chain and service operations, predictive analytics models for supply chain performance (Aifuwa *et al*., 2020), real-time machine learning risk dashboards (Filani *et al*., 2022), resilient logistics frameworks integrating predictive analytics and Internet of Things sensing (Anene & Clement, 2022), and segmentation and forecasting models for targeting effectiveness (Basnet *et al*., 2021) all exhibit architectures, streaming features feeding scored risk indices surfaced on dashboards, that are isomorphic to boiler health monitoring platforms. Even attribution research addressing bias in multi-touch models (Sanni, Atima, *et al*., 2022) and predictive segmentation under regulatory constraints (Atima *et al*., 2022) contribute transferable lessons on causal attribution and on deploying models in compliance-constrained environments, both live issues when efficiency losses must be attributed to specific degradation causes.

4.5. Data Preparation, Feature Engineering, and Model Lifecycle

Published model comparisons often understate the share of effort that data preparation consumes in real deployments. Plant historian data arrives with compression artifacts, irregular sampling, gaps from outages and communication failures, unit and tag inconsistencies across control system generations, and unlabeled operating modes. Before any modeling, pipelines must align time bases, reconstruct or flag missing intervals, detect steady-state versus transient operation, and join process data with maintenance records, fuel analyses, and laboratory chemistry results that live in entirely separate systems. Feature engineering then converts raw signals into physically meaningful inputs: corrected temperatures, section-wise heat absorption ratios, excess air, spray flows as a fraction of steam flow, cycling counts and ramp statistics, and cumulative exposure indices for chemistry and thermal events. Models built on such physics-informed features consistently outperform models fed raw tags, both in accuracy and in the interpretability that maintenance engineers require.

The model lifecycle extends well beyond first deployment. Boilers change: fuels switch, surfaces are cleaned or replaced, control logic is retuned, and instruments are recalibrated, and each change can invalidate a learned baseline. Mature programs therefore implement drift monitoring on model residuals, scheduled revalidation against recent known-good operation, retraining procedures with human review before promotion, and versioning that ties every alert to the exact model and data window that produced it. These practices mirror the disciplined software delivery and testing approaches reviewed in Section 4.6 (Borah *et al*., 2022; Mbonu *et al*., 2021b; Badmus *et al*., 2020) and the human-in-the-loop feedback structures discussed earlier (Ladapo, Dosunmu, *et al*., 2022). Governance of the model lifecycle, including documented ownership, change control, and audit trails for model decisions that influence inspection scope, is increasingly expected wherever analytics informs safety-relevant decisions, a point developed in Sections 4.7 and 5.1.

4.6. Data Infrastructure and Integration Architectures

Deployment of these techniques at plant scale requires an information architecture that moves data from sensors to decisions. The functional layering standardized in ISO 13374 for condition monitoring systems, comprising data acquisition, data manipulation, state detection, health assessment, prognostics, and advisory generation, remains the reference structure (ISO, 2003), complemented by the general condition monitoring guidance of ISO 17359. In modern implementations, data acquisition combines the distributed control system and plant historian with dedicated monitoring hardware and wireless sensor networks; edge devices perform signal processing close to the sensor; and cloud or on-premise analytics platforms host the models and dashboards. Instrumentation and control practice for steam plants is treated comprehensively by Basu and Debnath (2015). The communications layer matters as well, and studies of telecommunication deployment for network quality (Amayo & Popoola, 2017b) are relevant to the wireless backhaul on which distributed plant sensing increasingly relies.

Above the acquisition layer, the design of the analytics platform draws on enterprise information systems research. Risk-based business intelligence architectures (Mbonu *et al*., 2021a) and business intelligence dashboard frameworks for executive visibility (Sanni & Atima, 2021b) inform how boiler health and efficiency indicators are aggregated for plant and fleet management, while practical analytic tooling for profitability and performance analysis (Akin-Oluyomi *et al*., 2020) and frameworks for data-driven operations management (Efobi *et al*., 2021) describe the reporting layer through which maintenance value is communicated. Predictive capacity planning and resource utilization forecasting for multi-program IT portfolios (Edivri & Oteri, 2022) applies to sizing the compute and storage that continuous monitoring workloads demand. Delivery of the software itself benefits from disciplined engineering practice: comparative evaluations of DevOps tooling (Badmus *et al*., 2020), best practices for cloud migration in transforming organizations (Ladapo, Jooda, *et al*., 2022), digital transformation frameworks with embedded IT controls (Mbonu *et al*., 2020a), and applications of artificial intelligence in software testing (Borah *et al*., 2022; Mbonu *et al*., 2021b) collectively define how monitoring applications are built, validated, and evolved without disrupting plant operations. Two integration issues deserve emphasis. First, contextualization: raw signals must be tagged with operating state, load, fuel, and maintenance events for models to learn correctly. Second, workflow integration: predictive outputs create value only when they generate work orders in the computerized maintenance management system and inspection scope for planned outages.

Architecturally, the edge-versus-cloud question is settled in practice by a division of labor rather than a winner. Edge processing close to the sensor handles high-frequency signal reduction, local protection logic, and operation through network interruptions, while central platforms handle fleet-wide model training, long-horizon storage, and cross-plant benchmarking. Between them sits the plant historian and its contextual layer, which remains the system of record for process data in most facilities. The practical integration pattern that has emerged is therefore layered publication: edge devices publish condensed features rather than raw waveforms, the plant layer enriches them with operating context, and the central layer consumes contextualized features for analytics whose outputs flow back down as alerts and work orders. This layering also simplifies the security segmentation of Section 4.7, since each boundary crossing is a defined, inspectable interface rather than an ad hoc connection.

4.7. Cybersecurity and Data Governance for Monitoring Infrastructure

Connecting boiler instrumentation to analytics platforms extends the attack surface of what is safety-critical operational technology (OT), and the predictive maintenance literature is now inseparable from the OT security literature. Systematic reviews of securing operational technology networks in electric utilities under regulatory compliance regimes (Adegbite *et al*., 2020), security architecture models for information technology and OT convergence in regulated energy networks (Adegbite *et al*., 2022), and zero trust architectures for operational technology in critical infrastructure (Ahmed *et al*., 2021; Ogbole *et al*., 2021) define the reference protections for monitoring networks. Emerging threats specific to analytics itself are addressed by conceptual frameworks for adversarial machine learning in critical infrastructure (Adebayo *et al*., 2022), which warn that learned models can be manipulated through poisoned or spoofed sensor data. Privacy-centric security engineering models (Okoruwa *et al*., 2020) and lessons learned from offline assessment of security-critical systems (Ladapo *et al*., 2018) round out the design guidance. Operationally, plants adopt the mainstream enterprise security stack: security audit and risk assessment frameworks (Dosunmu & Ogundele, 2019), intrusion detection and prevention models (Dosunmu & Ogundele, 2020), incident response and digital forensics strategies for rapid containment (Dosunmu & Ogundele, 2021), threat intelligence integration for proactive defense (Dosunmu & Ogundele, 2022), enterprise log analytics with automated incident response (Mbonu, Iwuanyanwu, *et al*., 2019), and forensic analytics for detecting fraud and misuse over networked services (Mbonu *et al*., 2021).

Data governance is the second pillar. Monitoring platforms aggregate operational data across sites, vendors, and jurisdictions, which raises the questions treated in frameworks for legal and ethical risk modeling in enterprise data protection (Mbonu *et al*., 2018), comparative reviews of data protection regulation and secure cloud implementation (Mbonu, Aliliele, *et al*., 2019), data protection impact assessment models for multi-cloud infrastructure (Mbonu *et al*., 2022a), privacy-preserving data architectures for regulated industry analytics (Atakpa & Abolaji, 2022), and data privacy governance models for cross-border digital platforms (Annan, 2022). Access to plant data must be managed with the same rigor as access to plant control: identity and access management integration strategies for hybrid and multi-cloud estates (Mbonu *et al*., 2020), cloud identity and access governance optimization at enterprise scale (Mbonu *et al*., 2022b), and directory-based enterprise network management (Ladapo *et al*., 2019) supply the mechanisms, while infrastructure-as-code governance for secure cloud provisioning (Mbonu *et al*., 2020b) ensures the monitoring environment itself is reproducible and auditable. Finally, AI-enabled information technology general controls and audit automation (Mbonu *et al*., 2022) indicate how the integrity of analytic pipelines can be assured to the standard that regulated industries expect.

5. Organizational, Economic, and Regulatory Context

5.1. Safety Management, Risk Governance, and Regulatory Oversight

Boilers are high-hazard assets, and predictive maintenance is as much a safety program as a reliability program. The occupational safety literature therefore bears directly on how monitoring insights are converted into safe work. Conceptual models of data-driven occupational safety risk control in large energy infrastructure projects (Obriki & Arumosoye, 2018) and critical reviews of occupational safety management systems in oil and gas maintenance projects (Obogo *et al*., 2020c) frame the governance within which boiler maintenance is executed. Hazard identification is the front line: systematic reviews of hazard identification and risk control in construction and industrial projects (Obogo *et al*., 2019), advances in proactive hazard recognition and near-miss reporting systems (Obogo, Arumosoye, *et al*., 2021), and studies of near-miss and hazard observation data utilization (Arumosoye & Obriki, 2019) show how leading-indicator data, exactly analogous to condition monitoring data, predicts and prevents incidents. Conceptual models for incident prevention in industrial maintenance engineering environments (Obogo, Obriki, *et al*., 2021) make the connection explicit, and internal QHSE audit systems for industrial operations (Obogo *et al*., 2020a) provide the assurance layer.

Specific boiler maintenance activities inherit specific risk models. Heavy lifting during pressure part replacement is addressed by risk management models for heavy lifting and crane installation operations (Obogo *et al*., 2020b) and risk pathway models for lifting and rigging in heavy industrial construction (Arumosoye & Obriki, 2022). Work in hot environments around operating boilers is illuminated by integrated heat stress risk models for industrial operations in extreme environments (Arumosoye & Obriki, 2018). Emergency preparedness and evacuation system reviews (Obriki *et al*., 2022b) apply to boiler house design and outage planning. The human dimension is treated by frameworks for human error causation in high-risk activities (Obriki & Arumosoye, 2020), models explaining the recurrence mechanisms of unsafe behaviors on high-hazard worksites (Obriki & Arumosoye, 2022), and advances in workforce safety training models (Obriki *et al*., 2022a). Organizationally, contractor-heavy boiler outages benefit from governance-oriented models of contractor safety performance in multi-contract projects (Arumosoye & Obriki, 2020), reviews of contractor safety compliance systems in infrastructure projects (Obogo, Uduokhai, *et al*., 2021), and construction safety risk governance models for multi-contractor work (Obogo *et al*., 2019b). Leadership-driven safety culture transformation (Obogo *et al*., 2019a), frameworks linking management safety walkthrough frequency and coverage to culture outcomes (Obriki & Arumosoye, 2019), organizational learning based maturity models for continuous safety performance improvement (Arumosoye & Obriki, 2021), models for institutionalizing life-preserving safety practices across project organizations (Obriki & Arumosoye, 2021), and safety governance models for large facility operations (Obogo *et al*., 2022) together describe the organizational scaffolding that predictive maintenance programs must respect and can reinforce, since predicted failures that are removed before they occur are also incidents that never happen.

Regulatory oversight in other high-hazard transport and infrastructure sectors offers instructive parallels for boiler inspection regimes. Aviation research on predictive compliance monitoring using complaint and surveillance data (Adeyelu, 2018), adaptive safety management system implementation in developing economy contexts (Adeyelu, 2019), artificial intelligence driven risk quantification for airworthiness impacts (Adeyelu, 2020), enforcement frameworks for encroachment and unauthorized structures (Adeyelu, 2021; Adeyelu, 2022), and comparative benchmarking of certification compliance across regulators (Adeyelu & Dagodzo, 2022) collectively illustrate how data-driven, risk-based oversight is displacing purely calendar-based inspection, a shift that pressure equipment regulation is undergoing as risk-based inspection gains acceptance. At the enterprise level, the internal audit and risk governance literature, including technology-enabled internal audit quality models (Akomolafe & Agu, 2018), risk-based internal control frameworks (Akomolafe & Agu, 2019a), data-driven risk evaluation models (Akomolafe & Agu, 2019b), and integrated governance and compliance strategies for financial resilience (Akomolafe & Agu, 2019c), describes the second and third lines of defense within which asset risk models, including boiler RUL models, are validated and challenged.

5.2. Maintenance Supply Chain, Spare Parts Logistics, And Lean Operations

A prediction is only valuable if the organization can act on it, and acting on it requires materials, contractors, and logistics. The supply chain literature for energy and infrastructure is therefore an integral, if often overlooked, component of predictive maintenance capability. Models for inventory availability and plant uptime improvement in energy facilities (Okonkwo *et al*., 2018b) and conceptual models for materials readiness and maintenance-driven supply chains (Okonkwo, Agbabiaka, *et al*., 2021) address the direct link between spare parts positioning and the ability to execute condition-based work. Supply chain risk management models for engineering, procurement, and construction and gas processing projects (Agbabiaka *et al*., 2019) and supply chain resilience frameworks for critical infrastructure (Ogunwole *et al*., 2021) matter because boiler pressure parts have long and fragile lead times. Procurement effectiveness is treated by frameworks for strategic procurement optimization in oil and gas operations (Okonkwo *et al*., 2018a), regulatory-compliant procurement in high-risk energy environments (Okonkwo, Ogunwole, *et al*., 2021), cost reduction through contract negotiation and vendor governance (Okonkwo *et al*., 2019), negotiation optimization models for manufacturing procurement (Akinleye & Adeyoyin, 2022a), process automation frameworks for procurement efficiency and transparency (Akinleye & Adeyoyin, 2021), and supplier relationship management frameworks for strategic procurement objectives (Akinleye & Adeyoyin, 2022b; Ike *et al*., 2021). Data-driven vendor evaluation and bid selection using geospatial intelligence (Ahiaeke Patrick *et al*., 2021) and geographic information system enabled ERP procurement processes (Ahiaeke Patrick *et al*., 2020) show digitalization reaching the purchasing function itself, while models for demurrage elimination and port logistics efficiency (Okonkwo *et al*., 2020) are pertinent to imported capital spares. Sustainability constraints increasingly shape these decisions, as reflected in frameworks for sustainable procurement in local manufacturing (Efobi *et al*., 2022a) and decision frameworks reconciling chemical safety with circular economy targets (Okojie & Abioye, 2020).

Lean operations thinking connects the supply chain to the maintenance workflow. Lean supply chain practices for operational improvement (Ike *et al*., 2022), data-driven lean supply chain optimization models (Efobi *et al*., 2022b), and end-to-end visibility frameworks (Nnabueze *et al*., 2021) describe how waste is removed from the plan-schedule-execute-close maintenance cycle. At the level of the maintenance organization itself, adaptations of Lean Six Sigma for smaller enterprises (Ambali *et al*., 2021), the treatment of standard operating procedures as strategic assets (Eyetsemitan *et al*., 2022), cycle time reduction methods (Oyeleye *et al*., 2022), translation of regulatory requirements into executable workflows (Eyetsemitan *et al*., 2021), and multi-stakeholder governance alignment in joint operations (Eyetsemitan *et al*., 2020) are directly applicable to maintenance planning offices, which are frequently small teams coordinating many stakeholders under regulatory constraint.

5.3. Economic Evaluation, Financial Planning, and Decision Support

Predictive maintenance competes for capital and must justify itself in financial terms, which places it within the enterprise decision analytics literature. Conceptual frameworks for data-driven executive decision systems in strategic financial planning (Lawal & Oduleye, 2019b), decision models for capital allocation using financial analytics (Lawal & Oduleye, 2021a), and integration models aligning financial planning analytics with corporate strategy (Lawal & Oduleye, 2021b) describe the planning processes into which maintenance investment cases are submitted. Financial analytics driven enterprise value creation models (Lawal & Oduleye, 2018a) frame avoided downtime and fuel savings as value drivers, while analytical models for measuring return on investment under regulatory constraint (Sanni *et al*., 2020a) address the attribution problem of crediting savings to a monitoring program. Forecasting disciplines are shared: CRM-based sales forecasting model design (Dada *et al*., 2021b) and multinational cash flow consolidation with risk control (Dada *et al*., 2021a) use the same forecasting and consolidation machinery applied to maintenance budgets and outage cash flow across plants, and CFO-led strategic finance models for joint ventures (Isiekwu *et al*., 2021) are relevant where boiler assets are jointly owned. Compliance dimensions, including comprehensive financial reporting models for accountability (Medon & Oduleye, 2022), tax governance and cross-border compliance analytics (Lawal & Oduleye, 2018b), and risk assessment models for transfer pricing in multinationals (Lawal & Oduleye, 2019a), arise when monitoring services and spare parts flow across borders within corporate groups. More broadly, analytics-driven strategy frameworks under compliance and sustainability complexity (Sanni & Atima, 2021a), data-driven positioning frameworks in regulated professional sectors (Sanni *et al*., 2020b), and systematic reviews of product management in large-scale technology rollouts (Sanni *et al*., 2020c) offer semi-related but transferable guidance on how analytics products, of which a boiler health platform is one, are positioned, governed, and scaled inside organizations.

5.4. Energy Transition and Sustainability Context

Boiler predictive maintenance now operates inside an energy system in transition, and the surrounding literature conditions both the duty cycles boilers face and the standards to which their performance is held. Comprehensive reviews of smart grid architectures for high renewable penetration (Adenuga, 2022) and systematic reviews of control architectures for distributed energy resources (Komi & Adamolekun, 2022) describe grids in which thermal plants cycle more frequently, precisely the operating pattern that accelerates fatigue damage and raises the value of condition monitoring. Hybrid deep learning for wind power forecasting (Komi, 2021) exemplifies the forecasting stack that determines when thermal units will be dispatched, information that predictive maintenance schedulers increasingly consume. On industrial sites, integration of solar generation into small-scale manufacturing (Sunday & Omoegun, 2018) and optimization of load distribution in hybrid solar installations (Sunday & Omoegun, 2019) change the electrical environment of boiler auxiliaries, while programmatic strategies for renewable energy integration drawn from large-scale solar projects (Yeboah & Ike, 2020) and co-optimization of technical performance with community affordability in microgrids (Komi & Adeniji, 2020) indicate the wider socio-technical criteria against which energy asset decisions, including boiler life extension versus replacement, are now judged. Environmental co-benefits reinforce the maintenance case: every avoided efficiency loss is an avoided emission, and lifecycle risk assessment frameworks developed for produced water management in energy operations (Falegan & Aniebonam, 2022) exemplify the lifecycle environmental risk lens that is being extended to boiler water, blowdown, and ash streams.

The transition also reframes the strategic question that predictive maintenance answers. For many industrial boilers the relevant horizon is no longer indefinite operation but a bounded remaining service period, pending electrification, fuel conversion to hydrogen-ready or biomass firing, or heat recovery integration. Over a bounded horizon, the objective shifts from maximizing asset life to minimizing total cost and risk until a planned exit, which changes optimal maintenance policy in specific ways: life-limited components may be run closer to their limits under monitoring rather than replaced, capital repairs are weighed against conversion timelines, and monitoring data itself becomes an input to the retire-convert-retain decision by quantifying the true condition of the asset. Predictive maintenance thus serves the transition twice, first by keeping the existing fleet efficient and reliable while it is needed, and second by supplying the condition evidence on which rational transition sequencing depends.

5.5. Standards, Codes, and Inspection Regulation

Predictive maintenance of pressure equipment operates inside a dense framework of codes and standards, and program design must respect it. Construction and repair of boilers are governed by pressure vessel codes such as the ASME Boiler and Pressure Vessel Code and the European standards for water-tube and shell boilers, while in-service inspection and repair are administered under national and jurisdictional inspection regimes that historically prescribe fixed inspection intervals. Performance evaluation is codified in ASME PTC 4 (ASME, 2013), and condition monitoring system architecture and practice are addressed by ISO 13374 (ISO, 2003) and ISO 17359 (ISO, 2018). Above the technical layer, asset management standards in the ISO 55000 family frame maintenance as a value-driven, risk-based activity aligned with organizational objectives, which is precisely the framing under which predictive programs are justified.

The most consequential regulatory development for predictive maintenance is the gradual acceptance of risk-based inspection, in which inspection scope and interval are set from assessed probability and consequence of failure rather than from the calendar alone. Condition monitoring data is the natural evidence base for the probability side of that assessment, so the regulatory trend and the technological trend reinforce one another: better monitoring justifies differentiated inspection, and differentiated inspection creates demand for better monitoring. The same movement from prescriptive to risk-based, evidence-driven oversight is visible in the aviation safety regulation literature reviewed in Section 5.1, and pressure equipment jurisdictions are following a parallel path at their own pace. Programs should nonetheless be designed defensively: monitoring data supplements but does not replace statutory inspection until the jurisdiction explicitly allows it, and documentation quality, traceability of data, and validation of models are what ultimately persuade inspectors and insurers to give predictive evidence formal standing.

5.6. Implementation Pathway and Organizational Maturity

Synthesizing the practitioner literature and the organizational studies cited throughout this review, successful boiler predictive maintenance programs tend to follow a recognizable phased path. The first phase is assessment and prioritization: a criticality analysis ranks boiler systems and auxiliaries by consequence of failure, existing instrumentation and data infrastructure are audited, failure history is compiled, and a small number of high-value monitoring targets are selected. The second phase is a bounded pilot: instrumentation is added or connected for the selected targets, baseline models are built, alert workflows are defined with named owners, and success criteria are agreed in advance in terms of detections, avoided events, and efficiency recovered. The third phase is scaling: the pilot patterns are generalized across the boiler fleet, integration with the computerized maintenance management system is completed so that alerts generate work seamlessly, and governance of models, data, and security is formalized along the lines of Sections 4.6 and 4.7. Programs that skip the pilot discipline and attempt plant-wide deployment in one step feature prominently among reported failures.

Organizational maturity develops along several dimensions at once: instrumentation coverage, data infrastructure quality, analytic sophistication, workflow integration, and workforce capability. A useful maturity conception runs from reactive practice, through planned preventive practice, to condition-based practice on critical assets, to predictive practice with prognosis and scheduling integration, and finally to prescriptive practice in which recommended actions and their economic consequences are generated automatically for human approval. Progression is rarely uniform; a plant may be predictive on draft fans while still reactive on refractory. The maturity models developed in the safety culture literature (Arumosoye & Obriki, 2021) translate naturally to this setting, emphasizing that capability is built through organizational learning loops rather than purchased in a single procurement. Skills are the binding constraint most often cited: the intersection of boiler engineering, instrumentation, and data science is thinly populated, and successful organizations grow this capability deliberately through pairing, training, and retention rather than assuming vendors will supply it indefinitely.

Program management benefits from a compact set of key performance indicators that connect technical activity to business outcomes. Table 2 summarizes indicators commonly used to steer boiler predictive maintenance programs, spanning asset performance, program effectiveness, and readiness to act. The indicator set deliberately mixes leading measures, such as alert precision and spare parts readiness, with lagging measures, such as forced outage rate, so that the program can be steered before annual outcomes are known, in the same spirit as the leading indicator practice of the safety literature in Section 5.1.

Table 2: Representative key performance indicators for boiler predictive maintenance programs.

Indicator	Definition	Primary Use
Boiler efficiency (indirect)	Heat loss method efficiency with uncertainty bounds	Fuel cost and emissions performance tracking
Exit gas temperature residual	Deviation of corrected flue gas exit temperature from baseline	Early fouling and air heater degradation detection
Section cleanliness factors	Observed to expected heat absorption ratio per section	Localizing fouling, steering soot blowing
Forced outage rate	Unplanned unavailable hours per operating period	Lagging program outcome measure
Tube failure frequency	Confirmed tube failures per boiler-year by mechanism	Degradation mechanism management effectiveness
Alert precision	Share of predictive alerts confirmed as genuine on investigation	Model quality and analyst trust management
Predictive work ratio	Share of maintenance work orders originating from condition data	Program adoption and workflow integration
Spare parts readiness	Share of predicted interventions executable from stock or committed supply	Ability to act on predictions without delay
Verified cost avoidance	Audited value of avoided outages and recovered efficiency	Financial justification and reinvestment case

6. Application Scenarios and Reported Outcomes

To make the integration of the preceding sections concrete, this section presents three illustrative scenarios. They are composite teaching examples constructed from the patterns reported across the literature reviewed above, not case studies of specific named plants, and quantitative values are indicative.

6.1. Scenario: Economizer Fouling Detected Through Efficiency Residuals

A 120 tonne per hour gas and biomass co-fired boiler shows a slow rise in corrected flue gas exit temperature over six weeks, from a baseline residual near zero to plus 14 degrees Celsius, while the economizer section cleanliness factor declines from 0.97 to 0.88 and other sections remain stable. The efficiency analytics of Section 3.7 localize the problem to the economizer, and the fuel log shows a recent increase in biomass share, consistent with the ash chemistry mechanisms of Section 2. The predicted fuel penalty, computed continuously, reaches a level that justifies action, and the trajectory model forecasts that the cleanliness threshold for a load restriction will be reached in roughly three weeks. Planning uses the supply chain readiness of Section 5.2 to confirm cleaning contractor availability, and a short cleaning stop is scheduled into a low-demand weekend rather than being forced by a capacity shortfall in peak season. Post-cleaning, the residual returns to baseline, and the recovered efficiency is booked by the finance process of Section 5.3 as verified savings attributable to the program.

6.2. Scenario: Early Tube Leak Identified Acoustically And Contained

An acoustic monitoring array on a solid-fuel boiler furnace registers a persistent rise in high-frequency energy at two adjacent sensors, with the leak location algorithm placing the source near a soot blower lane in the secondary superheater. Makeup water trending shows no detectable change yet, indicating a very small leak, and the anomaly detection layer of Section 4 has flagged the pattern at high confidence with low historical false alarm rate at this sensitivity. Operations elects a controlled shutdown at the end of the production week rather than an immediate trip, accepting four days of monitored operation under a documented risk assessment consistent with the safety governance of Section 5.1. Inspection confirms a pinhole erosion leak from soot blower impingement, exactly the self-inflicted mechanism noted in Section 2, and repairs are completed in 48 hours with materials already staged under the materials readiness practices of Section 5.2. The counterfactual, established from the plant's own failure history, is a mid-campaign forced outage with secondary damage to neighboring tubes and a repair scope several times larger.

6.3. Scenario: Forced Draft Fan Bearing Degradation Prognosis

Wireless vibration nodes on a forced draft fan detect a developing bearing defect signature, with defect frequency amplitude doubling over five weeks. The prognostic layer fits a degradation trajectory and estimates remaining useful life at eight to eleven weeks with stated confidence bounds, comfortably beyond a planned maintenance stop six weeks out. The alert automatically raises a work order in the maintenance system per the workflow integration of Section 4.6, the bearing and seals are confirmed in stock, and the replacement is folded into the planned stop with no incremental downtime. Motor electrical signatures, interpreted against model-based expectations in the spirit of the machine modeling literature of Section 3.4 (Amayo, 2017), corroborate mechanical findings and rule out an electrical root cause. The fan case illustrates the quiet majority of predictive maintenance value: no drama, no forced outage, simply a failure that was converted into a routine task because its timing was known.

6.4. Reported Industrial Outcomes

Published case experience through 2022, while heterogeneous in rigor, points to consistent categories of benefit. Acoustic leak detection installations are repeatedly credited with converting forced outages into planned short stops by identifying leaks early enough to schedule repairs, with attendant reductions in secondary tube damage. Intelligent soot blowing driven by cleanliness analytics has reported efficiency gains typically in the range of a fraction of a percent to more than one percent, together with reduced soot blowing steam usage and reduced blower-induced erosion. Continuous efficiency monitoring programs commonly recover fuel losses caused by drifting excess air control and air heater leakage that had gone unnoticed under periodic testing. Across industries, systematic reviews of predictive maintenance report reductions in unplanned downtime and maintenance cost when programs are properly implemented (Zonta *et al.*, 2020), and boiler applications appear to conform to this pattern. It must be acknowledged that published results are subject to selection bias, since unsuccessful implementations are rarely documented, and rigorous before-and-after studies with controlled baselines remain uncommon.

Benefit accounting deserves the same rigor as the engineering. Avoided-outage value depends on a counterfactual, what would have happened without the detection, and defensible programs establish that counterfactual from the plant's own failure history and repair records rather than from generic industry figures: the typical escalation of an undetected leak, the typical secondary damage multiplier, the typical duration of a forced versus a planned repair. Efficiency benefits are more directly measurable but require honest baselining, since fuel prices, load profiles, and fuel mixes shift between the before and after periods, and a savings claim that ignores these confounders will not survive a finance review. The strongest programs therefore maintain a verified benefit register, jointly owned by engineering and finance as anticipated in Section 5.3, in which each claimed benefit is documented with its evidence, counterfactual, and calculation, and this register, rather than any dashboard, is what sustains executive support through budget cycles.

7. Discussion

Three cross-cutting observations emerge from this review. The first concerns the distinctive epistemic position of the boiler among industrial assets. Because a boiler is, thermodynamically, an instrumented energy balance, its routine operating data carries far more diagnostic content than that of most machines, and the marginal cost of extracting maintenance intelligence from data already collected for control and energy accounting is low. The consequence is that the entry point for boiler predictive maintenance is analytical rather than instrumental: substantial value is typically available from historian data and efficiency analytics before a single new sensor is installed, which inverts the common assumption that predictive maintenance begins with a sensor procurement. New instrumentation, from acoustic arrays to wireless vibration nodes to aerial inspection, then earns its place by covering the failure modes that the energy balance cannot see.

The second observation is that the semi-related literatures surveyed in Sections 4 and 5 are not decorative context but functional components of the capability. The anomaly detection economics worked out in fraud surveillance, the leading indicator discipline of safety science, the zero trust architectures of operational technology security, the materials readiness models of maintenance supply chains, and the capital allocation frameworks of enterprise finance each govern a link in the chain from measurement to realized value, and a weakness in any link caps the value of the whole. This systems character explains a pattern visible across reported implementations: technically similar deployments produce widely different outcomes, with the variance explained largely by organizational integration rather than by algorithm choice. It also suggests that research evaluation criteria in this field should broaden from model accuracy metrics toward end-to-end measures such as avoided events, verified savings, and decision lead time.

The third observation concerns evidence quality. The quantitative benefits reported through 2022 are consistent in direction and plausible in magnitude, but they rest mainly on implementer accounts, single-site before-and-after comparisons, and composite industry figures, with little independent replication and clear survivorship bias. The field would benefit from the evaluation discipline that adjacent domains have begun to adopt: pre-registered success criteria, counterfactual baselines established before deployment, uncertainty statements on all savings claims, and publication of unsuccessful implementations alongside successful ones. Until such evidence matures, prudent practitioners should treat vendor benefit figures as upper bounds, design their own pilots to generate site-specific evidence, and rely on the verified cost avoidance discipline described in Section 5.6 rather than on transplanted industry averages.

8. Challenges, Limitations, and Future Directions

Several obstacles temper the progress described above. Sensor survivability in the boiler environment is a persistent constraint; high temperatures, ash, vibration, and thermal cycling degrade instruments, and a predictive program can be undermined by unreliable data more easily than by imperfect models. Data quality and scarcity of labeled failures limit supervised learning, pushing practice toward anomaly detection with its attendant false alarm burden. Many industrial boilers are decades old and served by legacy control systems with limited historian coverage, making retrofit instrumentation and data integration a significant cost. Model interpretability matters more in this domain than in many analytics applications, because maintenance engineers must justify outage scope decisions with physical reasoning, which favors hybrid models over black boxes. Cybersecurity considerations, as reviewed in Section 4.7, constrain connectivity between operational technology networks and cloud analytics. Finally, organizational factors, including skills gaps at the intersection of boiler engineering and data science, supply chain readiness to act on predictions, and the absence of clear ownership of predictive alerts, are cited as frequently as technical factors in explanations of program failure.

Alarm management is a challenge important enough to name separately. Every additional model and sensor adds alert volume, and organizations that fail to manage precision find their maintenance engineers habituating to alerts exactly as control room operators habituate to nuisance alarms, at which point the genuine warning is missed for the noise. The remedies are known but demand discipline: alert thresholds set from the economics of investigation rather than from statistical convention, suppression logic aware of operating mode and maintenance state, alert ownership with response time expectations, and regular review of every alert outcome so that precision is measured and models are corrected. The fraud detection literature cited in Section 4.1 arrived at identical conclusions under identical pressures, and its triage practices are directly reusable.

A further limitation is the transferability gap between demonstrations and fleets. Models and thresholds tuned on one boiler seldom transfer unchanged to a sister unit with different fuel, controls, or degradation history, and the literature contains more single-asset demonstrations than validated fleet deployments. Related is the small-plant gap: the economics of monitoring have been proven mainly on large utility and heavy industrial boilers, while the far more numerous small industrial and commercial boilers remain largely uninstrumented because integration cost, not sensor cost, dominates at that scale. Both gaps are active research and product frontiers, and both are prerequisites for the fleet-level learning ambitions described later in this section.

Turning from limitations to opportunities, four directions appear most promising as of 2022. First, physics-informed machine learning, embedding conservation laws and heat transfer relations into learned models, promises better extrapolation and smaller data requirements than purely statistical approaches. Second, edge analytics on low-cost hardware will push detection intelligence to the sensor, reducing bandwidth needs and enabling monitoring of smaller boilers for which central analytics has been uneconomic. Third, fleet-level learning, in which models are trained across many similar boilers with transfer learning techniques, offers a route around the labeled data scarcity that constrains single-asset models. Fourth, the tightening linkage between maintenance analytics and decarbonization objectives, since efficiency degradation is directly an emissions problem, is likely to strengthen the business case and regulatory impetus for continuous thermal performance monitoring. Standardization of data models for boiler condition data, extending the ISO 13374 framework, would accelerate all of these developments, as would closer methodological exchange with the adjacent predictive analytics, safety science, and supply chain communities surveyed above.

Two further directions merit note. Prescriptive maintenance, the extension from predicting a failure to recommending and economically ranking the responses to it, is the natural next layer: given a remaining useful life distribution, an outage calendar, spare parts positions, contractor availability, and energy prices, an optimization layer can propose when and how to intervene and quantify the cost of each alternative, turning the maintenance planner's judgment into a reviewed decision rather than an unaided one. The decision-analytic and financial planning literatures reviewed in Section 5.3 supply the optimization and valuation machinery, and the primary obstacles are data integration and trust rather than algorithms. Second, autonomous and semi-autonomous inspection will continue to expand: confined-space aerial platforms, crawler robots for drum and header internals, and automated image analysis promise inspection coverage during short opportunistic windows that human entry cannot achieve, building on the aerial and geospatial foundations reviewed in Section 3.5.

Finally, the field needs shared evaluation infrastructure. Progress in machine learning fields accelerated when common datasets and benchmarks made methods comparable; boiler prognostics has no equivalent public benchmark, in part because failure data is commercially sensitive. Anonymized shared datasets of boiler degradation trajectories, standardized evaluation protocols specifying detection lead time and false alarm metrics, and reporting conventions for industrial case studies would allow the community to distinguish genuine methodological advances from favorable circumstances, and would give practitioners an objective basis for selecting among the rapidly multiplying commercial offerings.

9. Conclusion

Predictive maintenance of industrial boilers has advanced substantially through the convergence of two complementary information sources: condition monitoring technologies that observe the physical state of components, and thermal efficiency analytics that expose degradation through its energetic signature. The heat loss structure of boiler efficiency gives this asset class an unusual advantage, in that routinely available process data carries diagnostic content about fouling, combustion condition, and leakage, and modern analytics has converted that content from periodic reports into continuous, localized health assessment. Machine learning, prognostic modeling, and digital twin frameworks now provide credible pathways from data to remaining useful life estimates and maintenance decisions, and reported industrial experience demonstrates real reductions in unplanned outages and fuel consumption. This review has also emphasized that the predictive maintenance capability of a boiler owner is a system property: it depends on secure and well-governed data infrastructure, on safety and risk governance that converts predictions into safe work, on supply chains that can deliver parts and contractors when predictions call for them, on financial decision processes that recognize and fund the value created, and on an energy system context that increasingly rewards efficient, flexible, and well-maintained thermal assets. The most productive research frontier is the principled combination of physical models with data-driven learning, pursued with equal attention to the organizational systems that surround the algorithms.

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