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IMPACT OF ADVANCED LUBRICATION MANAGEMENT SYSTEMS ON EQUIPMENT LONGEVITY AND OPERATIONAL EFFICIENCY IN SMART MANUFACTURING ENVIRONMENTS

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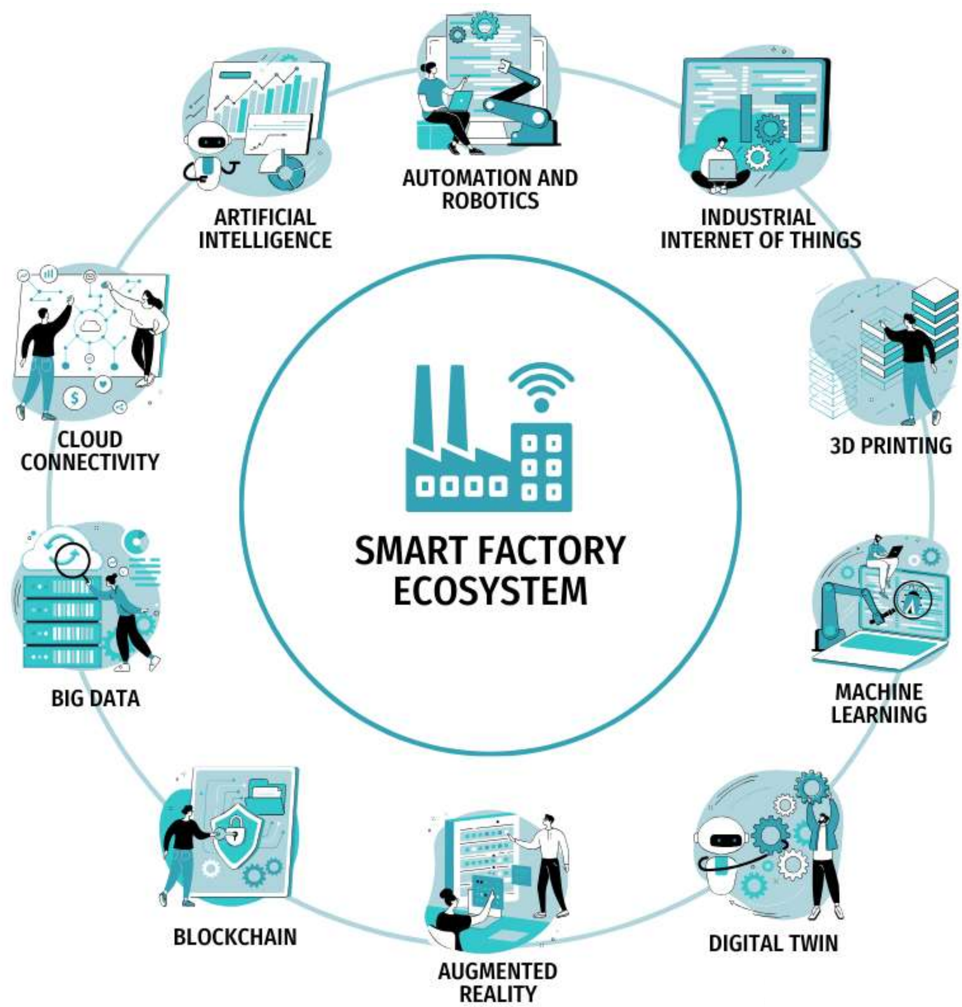
Abstract
Smart manufacturing depends on stable tribological interfaces. This systematic review synthesizes how Advanced Lubrication Management Systems (ALMS) affect equipment longevity and operational efficiency by integrating online oil and film-state sensing, automated dosing and filtration, contamination control, and connections to CMMS, MES, and digital twins. Following PRISMA 2020, we searched databases for records from 2010 to 2025, screened against predefined criteria, and appraised quality. In total, 115 studies met inclusion and we extracted outcomes for reliability, efficiency, energy, and fluids. Across 64 reliability-reporting papers, median gains were notable: mean time between failures increased by 19 percent and failure or hazard rates declined by 23 percent, underpinned by typical two-step improvements in ISO 4406 cleanliness codes and 35 percent lower moisture. Operational performance improved across 74 studies: Overall Equipment Effectiveness rose by 5.6 points, driven by availability (+3.4), with additional gains in performance (+1.7) and quality (+0.5); unplanned downtime fell by 27 percent and mean time to repair by 14 percent. Energy intensity decreased by 8.5 percent and by 12 percent in dip or splash-lubricated gearboxes; lubricant consumption fell by 22 percent and drain intervals extended by 35 percent. Economic reporting indicated a 13 month payback and first-year return of 86 percent. Moderator analyses show larger, steadier effects when ALMS are closed-loop and digitally integrated, when cleanliness and moisture targets are sustained, and when oil-state sensing is paired with contact-level regime detection. Findings position lubrication as a governed, data-driven control problem that advances reliability, throughput, energy efficiency, and sustainability in smart manufacturing.

Keywords
Advanced Lubrication Management Systems; Smart Manufacturing; Equipment Longevity; Overall Equipment Effectiveness; Condition-Based Maintenance; Oil Condition Monitoring;

INTRODUCTION

Smart manufacturing refers to digitally integrated, cyber-physical production environments that use pervasive sensing, connectivity, analytics, and automation to orchestrate processes with minimal human intervention (Lee et al., 2015). Within these environments, advanced lubrication management systems (ALMS) are socio-technical frameworks that combine high-fidelity condition monitoring of lubricants and tribo-surfaces, adaptive dispensing (e.g., centralized oil/grease systems), contamination control, and data-driven decision support to ensure the right lubricant, in the right quantity and condition, reaches the right point at the right time (Chen et al., 2015; Jiménez et al., 2019; Sun et al., 2023). The international relevance of ALMS is underscored by the global energy burden of friction and wear across transport, manufacturing, power generation, and residential sectors; seminal syntheses estimate that frictional losses consume roughly one-fifth of all produced energy, with substantial associated costs and emissions (Holmberg & Erdemir, 2017, 2019). By optimizing film formation and cleanliness, effective lubrication strategies can reduce energy use, extend component life, and curtail lifecycle emissions at scale impacts that resonate equally in high-income and emerging economies where industrial energy demand and asset intensity continue to grow (Holmberg et al., 2012). In smart factories, ALMS also interlock with cyber-physical production systems and enterprise platforms, enabling cross-line visibility of lubrication health and tying maintenance actions to quality and throughput objectives (Ara et al., 2022; Koley et al., 2019). This paper's focus on the "impact of advanced lubrication management systems on equipment longevity and operational efficiency" therefore sits at the intersection of tribology, reliability engineering, and data-centric industrial operations, and highlights a leverage point for nations seeking simultaneous gains in productivity, energy efficiency, and sustainability (Holmberg & Erdemir, 2017; Koley et al., 2019).

Figure 1: Overview of Smart factory



Lubrication functions as the fundamental safeguard of machinery longevity by governing transitions between friction regimes such as boundary, mixed, and hydrodynamic, thereby ensuring effective surface separation, thermal dissipation, and suppression of wear phenomena including fatigue, scuffing, and pitting (Jahid, 2022; Sun et al., 2021). With the advent of sophisticated metrological techniques, processes once hidden within tribological interfaces are now rendered observable: ultrasonic diagnostics and elastohydrodynamic (EHL) film-thickness measurements enable the precise characterization of micrometer-scale lubricant films under fluctuating dynamic loads, while advanced sensors that monitor viscosity and dielectric properties provide real-time insights into lubricant degradation processes driven by oxidation, fuel dilution, moisture ingress, and soot contamination (Akter & Ahad, 2022; Shi et al., 2022). Equally significant are developments in grease formulations, where refined rheological profiles, optimized base oils, novel thickener structures, and synergistic additive chemistries have demonstrably enhanced rolling-bearing performance and extended grease life, thus exemplifying the interplay between chemical innovation and component design (Arifur & Noor, 2022; Wu et al., 2021). These micro-level tribological advances resonate on a macro scale, as energy analyses of automotive drivetrains have revealed the immense proportion of global fuel consumption attributable to overcoming friction, thereby positioning lubrication quality as a determinant not only of component longevity but also of energy efficiency (Hasan & Uddin, 2022; Tandon et al., 2017). Within the domain of heavy industry, where frictional energy losses and wear-related costs represent a major economic burden, the argument for robust lubrication engineering, systematic monitoring, and precision management becomes particularly compelling (Rahaman, 2022; Zhao et al., 2021). Against this backdrop, the evolution of Advanced Lubrication Management Systems (ALMS) signifies a paradigm shift, as these integrated frameworks harmonize lubricant science with condition monitoring and automated supply mechanisms to consistently maintain machinery in optimal lubrication regimes while simultaneously inhibiting degradation pathways that would otherwise curtail mean time between overhauls.

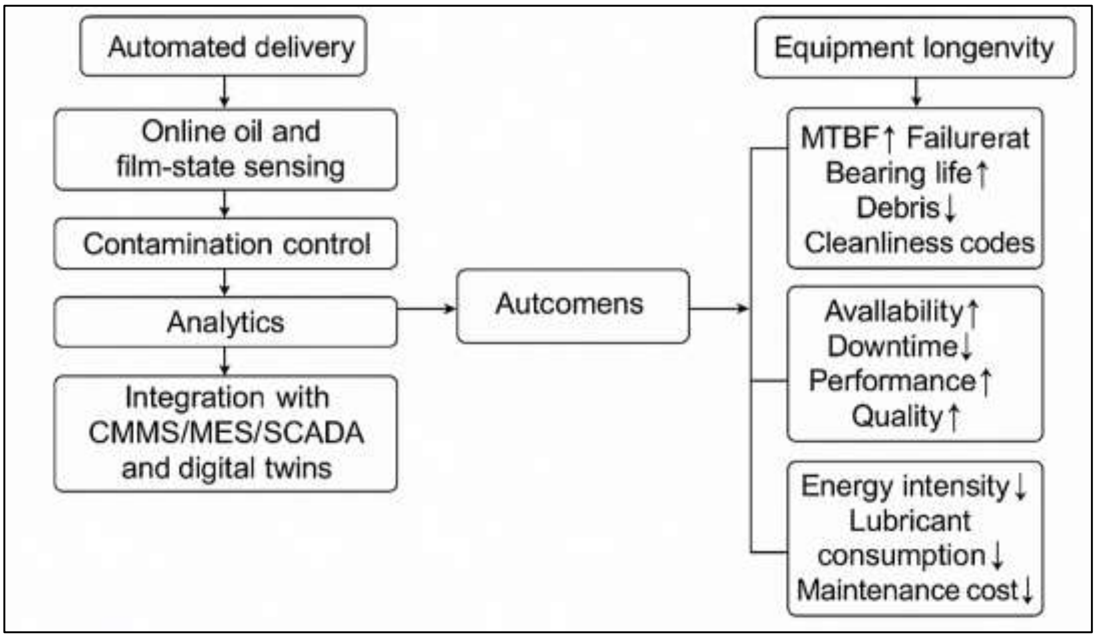
A hallmark of advanced lubrication management lies in the implementation of continuous, multi-modal oil condition monitoring (OCM), which integrates diverse sensing capabilities into a coherent diagnostic framework. Contemporary sensor arrays incorporate dielectric constant measurement, viscosity tracking, and surrogate parameters for total acid number (TAN) and total base number (TBN), complemented by particle counting and advanced wear-debris analytics, thereby enabling the timely detection of lubricant degradation and incipient mechanical wear (Rahaman & Ashraf, 2022; Zhu et al., 2017). The evolution of online debris monitoring technologies is particularly notable, having progressed from rudimentary single-coil inductive probes to sophisticated frequency-tuned, multi-coil architectures and microelectromechanical systems that not only discriminate between ferrous and non-ferrous particulates but also provide reliable estimates of particle size distributions under real-time flow conditions (Li et al., 2022; Islam, 2022). Supplementing these advancements are novel triboelectric oil health transducers, which cleverly exploit fluid motion to generate self-sustaining power for embedded sensors, thereby expanding the feasibility of widespread deployment across distributed lubrication points in complex machinery (Hasan et al., 2022; Ren et al., 2023). Collectively, these innovations mark a decisive transition from traditional intermittent laboratory-based analyses to continuous, in-line assessment, effectively shortening the potential-to-functional failure (P–F) interval and facilitating timely interventions that avert catastrophic wear progression. Contemporary reviews consistently underscore the diagnostic advantage of integrating multi-sensor feature sets with advanced signal processing and machine learning techniques, which enable robust and adaptive classification of lubrication states even under fluctuating operating conditions (Lu, 2020). Within the broader context of Advanced Lubrication Management Systems (ALMS), these enriched data streams empower rule-based and predictive decision-making frameworks that govern activities such as lubricant replenishment, re-greasing, reconditioning, and filtration, thereby elevating lubrication from a rigid schedule-driven routine to a dynamic, closed-loop, and evidence-based service paradigm that directly enhances both machine reliability and operational efficiency.

The integration of lubrication management within the smart-factory paradigm magnifies its strategic value by situating it within a fully connected and computationally enriched ecosystem. Cyber-physical production architectures, epitomized by frameworks such as the 5C stack, enable seamless interaction between sensorized assets, localized edge analytics, expansive cloud-scale models, and cognitive decision-making layers, thereby ensuring that lubrication-related data are not isolated but instead directly mapped to asset digital twins, maintenance work orders, and quality outcomes (Lu, 2017). At the enterprise scale, predictive maintenance platforms now demonstrate a pronounced trend toward synthesizing oil condition monitoring (OCM) with complementary diagnostic modalities such as vibration analysis, infrared thermography, and supervisory control inputs, with systematic reviews affirming the growing adoption of scalable, explainable pipelines that empower technicians to translate detection into decisive corrective action (Wang et al., 2019). Within such intelligent frameworks, Advanced Lubrication Management Systems (ALMS) serve not merely as passive data generators but also as active actuators: centralized units dynamically meter lubricant flow according to condition-based thresholds, automated filtration modules engage in response to particle counts, and contamination control measures are deployed via threshold-driven logic. The critical contribution of these integrated data streams is their alignment with manufacturing performance indicators, enabling the quantification of lubrication's downstream influence on key operational metrics such as downtime reduction, mean time to repair (MTTR), line speed consistency, scrap minimization, and energy consumption per production unit (Meng et al., 2022). Furthermore, when plants leverage common data environments through Manufacturing Execution Systems (MES), Computerized Maintenance Management Systems (CMMS), or Industrial Internet of Things (IIoT) hubs, lubrication events acquire enriched context by being linked with variables such as shift schedules, production recipes, and environmental parameters, thereby facilitating causal analysis and the design of repeatable improvement cycles. Recent advances in digital twin literature reinforce this potential by demonstrating the feasibility of simulating lubrication state trajectories in tandem with mechanical load profiles, a development that substantiates proactive re-lubrication and fluid conditioning strategies designed to preserve production stability and optimize overall efficiency (Schirru & Varga, 2022; Spikes, 2015; Wang et al., 2017).

Operational efficiency represents the arena in which the economic rationale for Advanced Lubrication Management Systems (ALMS) becomes most tangible, as the direct link between lubrication health and asset availability translates into measurable performance gains. Evidence from wind-energy manufacturing chains demonstrates how gearbox and bearing conditions constitute dominant sources of downtime, while comparative reviews emphasize that oil analysis substantially enhances vibration and acoustic diagnostics by revealing wear mechanisms and contamination phenomena that remain imperceptible to kinematic-based monitoring alone, thereby reducing diagnostic false negatives and enabling timely, targeted interventions (Wakiru et al., 2019). Complementary engineering models detailing gearbox thermal dynamics and lubrication flow patterns further highlight how the intricate coupling of temperature and viscosity governs film integrity and energy efficiency under variable loads, insights that have informed the calibration of OCM thresholds and replenishment strategies (Abudaida et al., 2020; Beamish et al., 2022). By correlating lubrication condition indicators with overarching production metrics such as Overall Equipment Effectiveness (OEE) and its sub-dimensions of availability, performance, and quality, manufacturers gain the capacity to quantify how ALMS alleviates process bottlenecks, enhances yield stability, and fortifies continuous operations (Li et al., 2024; Li et al., 2021). The broader industrial literature, spanning both automotive and process sectors, consistently signals that leveraging real-time OCM streams to trigger just-in-time re-lubrication and contamination control, rather than relying on rigid calendar-based maintenance routines, yields substantial reductions in unplanned stoppages and overall energy intensity (Zonta et al., 2020). These outcomes are further amplified when multi-sensor fusion architectures and deep learning pipelines are employed to capture subtle signatures of lubricant degradation and early wear progression under highly variable load conditions, a domain where simplistic single-parameter monitoring rules frequently prove inadequate (Lei et al., 2018; Liskiewicz et al., 2023). In this way, ALMS transforms lubrication from a background maintenance task into a strategic lever for operational resilience, economic efficiency, and sustainable industrial performance.

A consistently influential determinant of both machine longevity and operational efficiency is the cleanliness of lubricating fluids, as decades of experimental and applied research across hydraulic systems and tribological interfaces unequivocally demonstrate that solid particle contamination undermines pump, valve, and bearing performance by heightening friction, distorting clearances, and accelerating fatigue mechanisms, all of which manifest in increased energy consumption and shortened service intervals (Ahmad & Kamaruddin, 2012). Tribological investigations into contaminated lubrication films further reveal that surface engineering, such as strategic texturing, in concert with tailored lubrication strategies, can preserve load-carrying capacity and attenuate wear despite particulate intrusion, thereby underscoring the critical role of engineered surfaces within the broader architecture of Advanced Lubrication Management Systems (ALMS) (Guegan et al., 2019). In domains such as heavy industry and mobile hydraulics, where exposure to environmental contaminants is frequent and maintenance discipline can vary widely, the adoption of contamination-aware ALMS integrating in-line particle sensing, adaptive filtration technologies, and rigorous handling practices has been repeatedly associated with tangible gains in component longevity and overall process stability (Jiang et al., 2021). These outcomes affirm that fluid cleanliness policies should not be relegated to routine housekeeping but instead regarded as strategic enablers of production excellence. At the scale of smart-factory operations, sustained lubrication cleanliness directly correlates with a reduction in micro-stoppages, smoother line speed trajectories, and enhanced product uniformity, outcomes made possible because lubrication regimes are preserved within favorable operating zones that minimize wear and stabilize energy transfer (Dwyer-Joyce et al., 2011). In this light, cleanliness emerges as both a preventive safeguard and a performance amplifier, integral to aligning ALMS with the dual goals of reliability and efficiency in modern industrial systems.

Figure 2: Advanced Lubrication Management Systems (ALMS) on Equipment Longevity



This literature review pursues a clear set of objectives focused on establishing what advanced lubrication management systems (ALMS) are, how they operate within smart manufacturing, and what measurable effects they have on equipment longevity and operational efficiency. First, it aims to define and bound ALMS conceptually and technically, distinguishing their core elements automated delivery, online oil and film-state sensing, contamination control, analytics, and integration with CMMS/MES/SCADA and digital twins so the term is used consistently across studies. Second, it develops a structured taxonomy and maturity model for ALMS that organizes technologies (e.g., centralized/point-of-use systems, particle/viscosity/moisture sensors, rule-based vs. data-driven control), data pipelines (edge, cloud), and organizational capabilities (workflows, skills, governance).

Third, it systematically maps and appraises the empirical evidence base using transparent inclusion criteria and a quality rubric, extracting common outcome variables, study designs, and contexts. Fourth, it quantifies effects on longevity by harmonizing metrics such as MTBF/MTTF, failure rate, bearing L10 life, debris generation, and cleanliness codes, and where compatible computing percent changes or standardized effects. Fifth, it quantifies effects on operational efficiency by aligning lubrication interventions with OEE components (availability, performance, quality), downtime and MTTR patterns, energy intensity, lubricant consumption, and maintenance cost. Sixth, it examines moderators that shape ALMS performance, including equipment class (bearings, gearboxes, hydraulics, compressors), load and duty cycles, environment, lubricant formulation, filtration and sealing practice, data quality and sampling cadence, and depth of integration with production systems. Seventh, it evaluates economic and sustainability dimensions through life-cycle cost framing, identifying cost components and benefit streams associated with uptime gains, energy reduction, and lubricant stewardship. Eighth, it assesses data and interoperability requirements (standards, identifiers, contextual metadata) necessary to link lubrication events with asset health and production outcomes, promoting reproducible analytics. Ninth, it synthesizes implementation enablers and barriers across people, process, and technology, translating evidence into a concise measurement framework and KPI set suitable for benchmarking. Tenth, it articulates a conceptual logic model that connects ALMS actions to tribological states, reliability trajectories, energy use, and OEE. Through these objectives, the review addresses three guiding questions: what measurable impact ALMS have on equipment longevity; what measurable impact they have on operational efficiency; and under which technical and organizational conditions those impacts are most pronounced and repeatable within smart manufacturing environments.

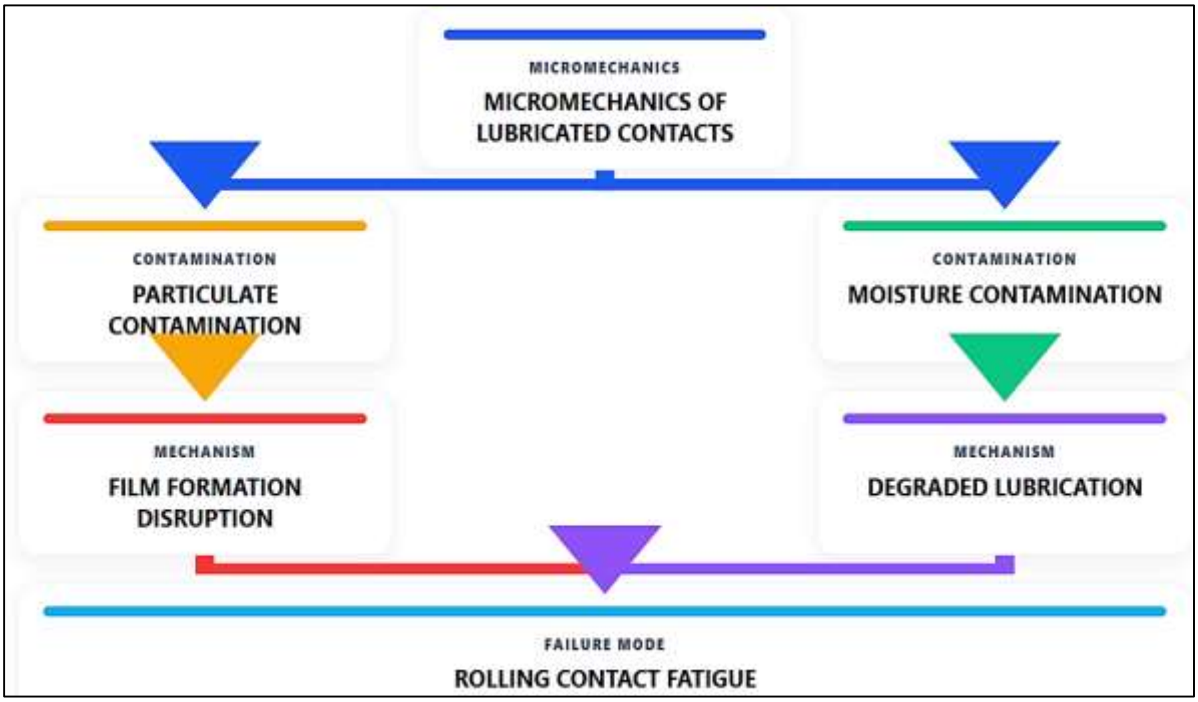
LITERATURE REVIEW

The scholarly literature on advanced lubrication management systems (ALMS) spans tribology, reliability engineering, and smart manufacturing, converging on a shared objective: controlling the state of the lubricant–surface interface to stabilize performance and extend equipment life within cyber-physical production environments. Across sources, ALMS are characterized not as a single device but as an integrated stack: sensing (e.g., viscosity, dielectric constant, moisture, particle counting, ferrous wear, and in-situ film thickness by ultrasonics), actuation (centralized or point-of-use automatic lubrication, electro-pneumatic metering, and programmable filtration/dehydration), decision logic (rule-based thresholds and data-driven models for condition-based lubrication), and system integration (event and work-order linkage through CMMS/MES/SCADA, with optional digital-twin orchestration). Two families of outcomes dominate: equipment longevity captured via MTBF/MTTF, failure rate, bearing L10 life, wear-debris rates, and cleanliness codes and operational efficiency captured via OEE and its availability/performance/quality components, downtime and MTTR patterns, energy intensity, lubricant consumption, maintenance cost, and scrap. Empirical studies are reported across bearings, gearboxes, hydraulics, compressors, conveyor lines, and continuous-process units, with duty cycles and ambient conditions shaping both the failure physics and the value proposition of ALMS. A consistent thread is the shift from calendar-based routines to condition-based lubrication, where multi-parameter oil and film monitoring provides earlier and more precise control actions; contamination control emerges as a central mediator because particulate and moisture ingress accelerate wear and degrade rheology, undermining both longevity and efficiency. Methodologically, the evidence base mixes lab-to-field pipelines, single-site industrial case studies, cross-sectional surveys, and system-level simulations, alongside systematic reviews in predictive maintenance and Maintenance 4.0. Recurrent limitations include heterogeneous reporting of baselines, inconsistent KPI definitions, short observation windows, small samples, and limited use of counterfactual or quasi-experimental designs, all of which complicate effect-size harmonization. Interoperability and data governance (e.g., contextual metadata, asset identifiers, time alignment) are noted as prerequisites for linking lubrication events to production outcomes in a reproducible way, as are human factors such as technician training and change management. Against this backdrop, the present review organizes the field around eight subtopics tribology and contamination control; ALMS architecture; condition-based lubrication; integration with plant information systems; standards and best practices; longevity outcomes; efficiency and sustainability outcomes; and economics, adoption barriers, and enablers so that mechanisms, magnitudes, and boundary conditions of ALMS impact can be synthesized coherently for smart manufacturing environments.

Tribology and Contamination Control in Smart Manufacturing

Within the landscape of smart manufacturing, the micromechanics of lubricated contacts continue to underpin reliability, as even minimal contamination in the form of particulates or trace moisture can destabilize elastohydrodynamic (EHL) interfaces, creating localized stress concentrations, surface indentations, and accelerated progression of rolling contact fatigue (RCF). Empirical field inspections of bearings in service environments consistently reveal that particle-induced indentations disrupt the continuity of film formation, thereby acting as preferential crack initiation sites that directly link oil cleanliness to bearing damage mechanisms and service life reduction (Morales-Espejel & Zhou, 2024). Moisture intrusion presents a parallel and equally insidious hazard, as dissolved water, emulsified droplets, or free-phase ingress alters lubricant viscosity, compromises thermal transport efficiency, and perturbs boundary chemistry, collectively eroding hydrodynamic load-carrying capacity and pushing contacts into mixed or boundary lubrication regimes under otherwise unchanged operational duty cycles (Harika et al., 2013). These transitions intensify both near-surface shear stresses and subsurface orthogonal shear fields, which are widely recognized as principal drivers of micropitting and micro-spall propagation within hardened tribological surfaces. At the micro-scale of an EHL conjunction, water contamination can further reorganize film topology dynamically, thickening grease films momentarily as droplets traverse the contact zone before causing thinning as two-phase emulsions relax, thereby generating unsteady lubrication states that elude conventional film-thickness control strategies (Kon et al., 2018). Collectively, these mechanistic pathways elucidate why contamination control is elevated from a maintenance afterthought to a fundamental design consideration in smart-factory settings, where operational uptime is monetized in minute-scale increments and component load paths are increasingly lightweighted to maximize energy efficiency (Harika et al., 2013). In such environments, rigorous fluid integrity management becomes not only a condition for extending component longevity but also a cornerstone of resilient, high-efficiency production.

Figure 3: Tribology and Contamination Control Pathways in Smart Manufacturing



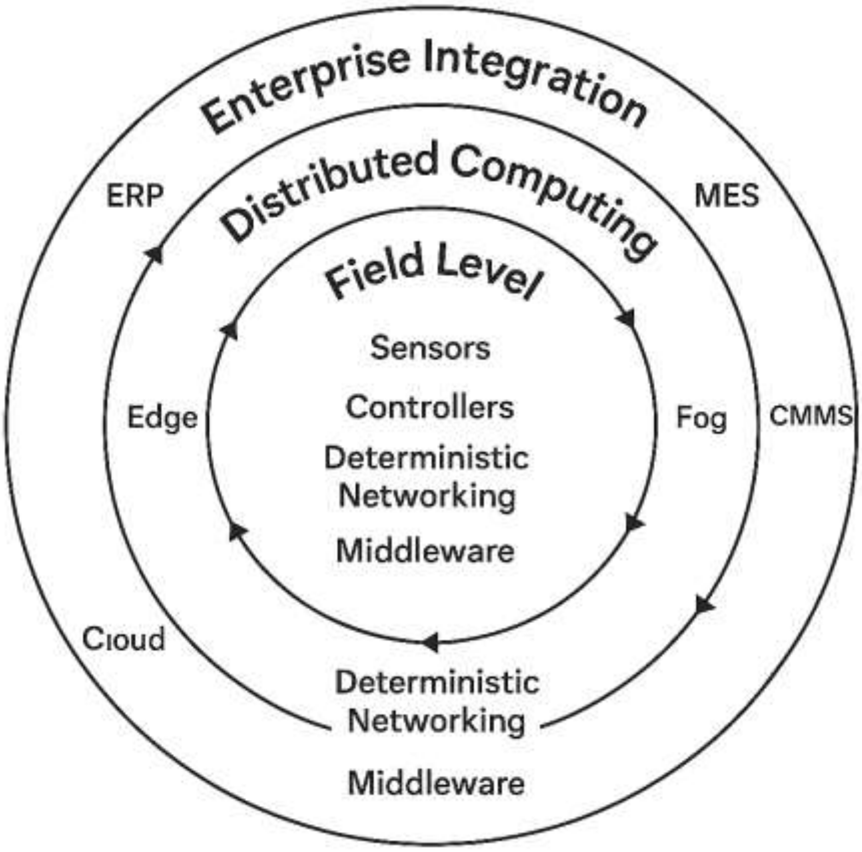
A second critical pillar of contamination control in lubrication management lies in the timely detection and mitigation of chemically driven oil degradation, with varnish formation representing one of the most problematic outcomes. Varnish precursors, typically highly oxidized and often polar oil-soluble species, destabilize additive chemistries, agglomerate under unfavorable thermal gradients, and eventually deposit as adherent films that impair servo valve function, obstruct narrow fluid clearances, and raise localized bearing temperatures, thereby accelerating the onset of mechanical distress. Since the solubility of these precursors is strongly influenced by temperature and solvent environment, membrane patch colorimetry (MPC) has gained wide adoption as a practical field indicator of varnish potential, although the technique is known to be sensitive to pre-filtration and sample-handling conditions (Kon et al., 2018). Recent refinements to MPC protocols for aged hydraulic fluids demonstrate that the traditionally lengthy incubation times can be shortened substantially without compromising diagnostic accuracy, a development particularly advantageous in smart-manufacturing contexts where maintenance workflows demand agility and rapid decision-making (Pravda et al., 2024). Beyond procedural improvements, the wider varnish research corpus underscores the complex interplay of oxidation kinetics, metal-catalyzed reactions, and trace water contamination in accelerating the formation of insoluble bodies and their subsequent deposition, processes that directly contribute to filter plugging, heat transfer inefficiency, and the erosion of operational reliability in high-duty industrial systems emblematic of Industry 4.0 environments (Hong & Jang, 2023). In parallel, materials engineering innovations are extending the available toolkit for varnish and degradation control: advanced selective and superhydrophobic separation media now facilitate highly efficient, inline extraction of dispersed water from lubricating oils, thereby neutralizing one of the most insidious accelerants of both tribological wear and chemical degradation (Zhao et al., 2020). Taken together, these advances reveal that proactive chemical diagnostics and material-based interventions are indispensable components of contamination-aware Advanced Lubrication Management Systems, ensuring both lubricant integrity and sustained production efficiency.

Translating contemporary insights on contamination dynamics into resilient industrial practice necessitates closing the loop between ingress, detection, and corrective action within cyber-physical maintenance frameworks, thereby embedding contamination control as an active dimension of smart-factory reliability. On the control front, active cleanliness management has emerged as a cornerstone, where judicious selection of filtration β-ratings, strategic deployment of return-line and off-line kidney-loop configurations, and precise targeting of cleanliness codes can significantly extend the service life of mechatronic assets, provided these measures are carefully harmonized with duty-cycle demands and component sensitivity profiles (Zhang et al., 2018). Complementing such control mechanisms, the sensing layer must deliver high sensitivity to contamination-related events: experimental work demonstrates that acoustic-emission and vibration-based techniques are adept at detecting particle ingress in journal-bearing systems, frequently providing earlier and more distinct signatures than broadband vibration monitoring for the onset of abrasive or dent-inducing transients. At the chemical interface, moisture exerts a more profound influence than simple viscosity dilution, as it actively depletes anti-wear and antioxidant additives through hydrolysis and competitive adsorption at tribological surfaces, thereby reshaping boundary-film composition and altering frictional behavior; recent tribochemical investigations quantify these depletion trajectories under water ingress, reinforcing the imperative of integrated moisture management and additive health surveillance within advanced lubrication strategies (Deng et al., 2024; Poddar & Tandon, 2019). Synthesizing these strands yields a modern contamination-control playbook tailored for smart manufacturing environments: define and enforce cleanliness targets that reflect elastohydrodynamic (EHL) film thickness thresholds relevant to bearings and gears; monitor moisture and oxidation precursors using validated, rapid-response methodologies; and integrate these signals seamlessly with filtration, separation, and scheduling protocols to ensure that tribological risks are anticipated and mitigated proactively rather than addressed reactively (Deng et al., 2024; Poddar & Tandon, 2019). In this configuration, contamination management becomes a predictive, closed-loop capability that sustains equipment health and stabilizes production efficiency.

Architecture of Advanced Lubrication Management Systems (ALMS)

A contemporary ALMS is best understood as a layered cyber-physical architecture that spans instrumentation at the machine, deterministic industrial networking, middleware for data modeling and exchange, and enterprise integrations for planning and execution. At the field level, oil condition, flow, pressure, temperature, particle contamination, and valve/actuator states are acquired continuously and orchestrated by microcontrollers and PLCs. Deterministic transport and time synchronization are essential here because dosing cycles and interlocks must be coordinated at sub-millisecond scales; this is why many manufacturers adopt OPC UA with Publish–Subscribe semantics and, increasingly, OPC UA over Time-Sensitive Networking (TSN) for field-level communication (Lo Bello & Steiner, 2019; Pfrommer et al., 2018). Above the device tier, ALMS middleware normalizes measurements, exposes a typed information model, and brokers command/feedback with publish–subscribe topics or client–server calls across mixed vendor fleets. Comparative studies show that MQTT can be extremely efficient for lightweight telemetry, whereas OPC UA adds rich data modeling and companion specifications needed for interoperable lubrication semantics across pumps, metering devices, and machine assets (Rocha et al., 2019). When real-time control logic must span distributed stations (e.g., sequencing multi-point metering across a transfer line), OPC UA Programs combined with TSN offer a vendor-neutral pattern for stateful, long-running tasks with bounded latency and jitter, aligning machine coordination with lubrication timing constraints (Eymüller et al., 2020). In sum, the base of the ALMS stack binds precise sensing/actuation to deterministic networking and semantically rich middleware so that dosing decisions remain synchronized with equipment dynamics(Eymüller et al., 2020).

Figure 4: Cycle Architecture of Advanced Lubrication Management Systems (ALMS) Across Field



The subsequent architectural layer of Advanced Lubrication Management Systems (ALMS) distributes computational tasks across edge, fog, and cloud resources, ensuring that critical control functions remain proximate to machinery while analytical capabilities scale elastically to accommodate enterprise-wide intelligence. Edge nodes, typically industrial PCs or embedded gateways situated adjacent to operational assets, handle first-mile data ingestion, buffering, rule-based alerting, and rapid diagnostics such as detecting viscosity deviations or flow anomalies, thereby reducing reliance on wide-area network latency and maintaining immediate operational responsiveness (Shi et al., 2016). Fog nodes serve as intermediate aggregators, consolidating data streams from multiple cells or production lines, hosting microservices for model deployment such as asset-specific regressions correlating wear rates with particle counts and implementing cross-machine coordination strategies that dynamically adjust lubrication dosing schedules based on shared operating conditions (Puliafito et al., 2019). Cloud platforms further extend the system's reach, integrating multi-site telemetry for fleet benchmarking, model retraining, and enterprise-level decision support, while high-velocity streaming engines ingest sensor outputs from oil condition monitors and pump controllers to support both near-real-time and historical analyses (Atlam et al., 2018). This edge–fog–cloud continuum allows ALMS to sustain rapid control loops essential for lubrication safety and efficiency at the local level, while leveraging centralized resources for pattern discovery, digital twin updates, and long-horizon optimization. From an architectural perspective, message buses decouple data producers sensors and PLCs from consumers including rules engines, dashboards, and historians, and containerized microservices ensure service isolation, maintainability, and upgrade flexibility. Schematized data topics, for instance via OPC UA companion models transmitted over PubSub protocols, combined with tiered streaming storage, enable sub-second actuation alongside multi-year reliability studies within the same pipeline, illustrating how distributed computing paradigms reconcile immediate operational needs with strategic intelligence and evidence-based maintenance planning.

An Advanced Lubrication Management System (ALMS) achieves operational significance only when fully integrated into production and maintenance execution frameworks, ensuring that lubrication intelligence drives tangible outcomes across the enterprise. At the operational layer, the platform must interface bidirectionally with Computerized Maintenance Management Systems (CMMS) or Enterprise Asset Management (EAM) tools to manage work orders and spare parts, with Manufacturing Execution Systems (MES) to synchronize scheduling and setup states, and with Enterprise Resource Planning (ERP) systems to capture cost data and support compliance documentation. Research on Maintenance 4.0 and Total Productive Maintenance (TPM) integration within Industry 4.0 contexts highlights that such linkages convert raw sensor telemetry into actionable maintenance plans, embed lubrication checkpoints into standardized workflows, and align dosing logic with takt time, quality gates, and production changeovers (Atlam et al., 2018; Tortorella et al., 2021). From an implementation standpoint, the underlying information model must map all lubrication assets including pumps, manifolds, metering units, and filters along with their health indicators, to the asset hierarchies recognized by CMMS, while the control plane exposes safe, auditable commands such as purge or calibration, which are enforced through interlocks. Early machine-tool deployments illustrated this blueprint by integrating dedicated lubrication control units that fused temperature and tribological signals to trigger pump cycles, provided real-time status displays to operators, and documented lubricant consumption to support precision machining and sustainability objectives, principles that now extend to IIoT-native ALMS architectures across both discrete and process industries (Sparham et al., 2014). Mature implementations thus encapsulate three core elements: deterministic and interoperable field connectivity; a distributed edge–fog–cloud analytics fabric; and seamless integration with CMMS, MES, and ERP systems, collectively enabling lubrication intelligence to extend asset life, reduce unplanned downtime, and elevate overall equipment effectiveness (Sahal et al., 2020).

Condition-Based and Predictive Lubrication

Condition-based and predictive lubrication (CBPL) reframes greasing and oil-service actions from fixed intervals to data-triggered interventions that reflect the actual state of the lubricant film and the tribo-system it protects. In smart manufacturing environments, CBPL relies on multi-modal sensing to infer lubrication sufficiency linking measurable proxies (dielectric constant, viscosity, density, temperature, wear debris, and high-frequency acoustic signatures) to physically meaningful lubrication regimes. Integrated, in-line oil sensors make these proxies available continuously; for instance, multi-parameter probes embedded in hydraulic circuits have shown strong diagnostic value, with dielectric constant being particularly sensitive to moisture ingress and varnish formation, while viscosity, density and temperature provide complementary context for state estimation (Hong & Jeon, 2022). At the interface scale, acoustic-emission (AE) sensing is well suited to distinguish hydrodynamic, mixed, and boundary lubrication by tracking shifts in high-frequency energy and kurtosis features associated with asperity interaction; classification studies in journal bearings demonstrate reliable regime separation using AE features and supervised learners (Mokhtari et al., 2020; Poddar & Tandon, 2019). AE has also proven useful in large rotating assets, where its earlier response to lubrication perturbations can shorten detection latency relative to conventional vibration-only monitoring (Cornel et al., 2021). Together, these modalities enable a layered CBPL stack asset-level oil quality and contamination monitoring, contact-level regime detection, and controller-level logic to trigger replenishment or oil-change actions precisely when the risk of film failure, starvation, or contaminant-accelerated wear becomes material (Cornel et al., 2021; Mokhtari et al., 2020; Poddar & Tandon, 2019).

Figure 5: Process–Output Matrix for Condition-Based and Predictive Lubrication (CBPL)

Processes	Outputs
Multi-modal Sensing →	Lubricant and Machine Health Data
Condition Monitoring →	Lubrication Regime Detection
Predictive Modeling →	Remaining Useful Life Estimation

Predictive lubrication augments condition indicators with prognostics to forecast remaining useful life (RUL) of oils and to anticipate when re-greasing or drain-and-fill will restore design film performance at minimal cost. A foundational thread derives physics-guided observation models that link contamination (e.g., particles, water) and oxidation to online sensor outputs (viscosity, dielectric constant), then embeds those models in Bayesian/particle-filter estimators to produce real-time oil-health trajectories and RUL estimates; this approach has been demonstrated for wind-turbine drivetrain oils using commercially available sensors (Zhu et al., 2013; Zhu et al., 2015). Data-centric methods complement the physics layer: dynamic principal component analysis fused with proportional hazards modeling has been used to project oil failure risk from multivariate condition streams, enabling risk-based service timing under variable duty cycles (Du et al., 2019). On the contact side, AE-driven classifiers and regime identifiers can be coupled with regreasing logic to avoid over- and under-lubrication, while multi-sensor fusion (AE + oil quality + temperature/speed) improves observability of early boundary-film onset. Case evidence shows that when AE features are trended in tandem with oil-quality indicators, the combined signal captures both supply-side degradation (oil condition) and demand-side stress (load/speed transients) to better predict when replenishment will materially lower friction and temperature (Hasan et al., 2022; Mokhtari et al., 2018).

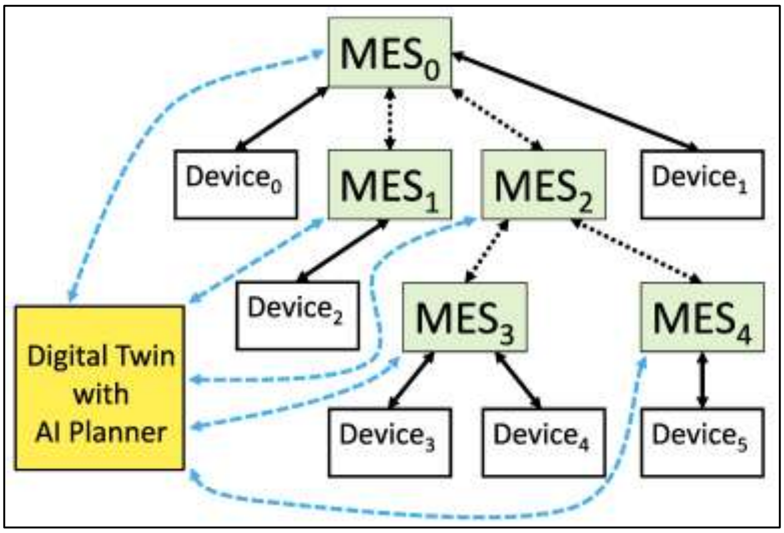
A central operational challenge in condition-based predictive lubrication (CBPL) is distinguishing routine variability from actionable anomalies linked to lubricant starvation, contamination, or film collapse, ensuring that predictive models inform interventions such as re-greasing, bleed/flush, or oil change rather than triggering alarms alone. Controlled experimental studies on journal-bearing systems demonstrate that acoustic-emission (AE) and vibration-derived features can reliably detect particle contamination and lubrication deficits, while machine-learning classifiers effectively differentiate between cavitation, contamination, and starvation states, each of which necessitates a tailored response (Redwanul & Zafor, 2022; Poddar & Tandon, 2021). In practical deployment, AE-based regime detection can be integrated with dosing logic, for instance ceasing greasing once the AE baseline plateau is reached to avoid over-lubrication, whereas remaining useful life (RUL) forecasts derived from oil-quality monitoring guide drain-and-fill operations before additive depletion or varnish formation elevates friction and temperature beyond safe operational thresholds. As systematic reviews of AE-based monitoring expand high-fidelity taxonomies of lubrication phenomena including feature engineering approaches, waveform analyses, and model interpretability evidence supporting robust CBPL policies continues to grow, enabling standardized trigger and stop rules with confidence-bounded maintenance timing in interconnected smart-factory environments (Ma et al., 2025; Rezaul & Mesbaul, 2022). Collectively, these insights indicate that coupling continuous oil-state sensing, contact-level regime recognition, and probabilistic RUL estimation allows lubrication interventions to be precisely aligned with the physical dynamics of film formation and degradation, thereby enhancing bearing life, maximizing throughput, and reducing both consumable usage and unplanned downtime.

CMMS/MES/SCADA and Digital Twins

Smart lubrication initiatives achieve maximum impact when fully embedded within plant information flows encompassing asset hierarchies, event streams, work orders, and performance dashboards rather than functioning as isolated point solutions. Standards-based integration minimizes the need for custom middleware and ensures that condition data, such as viscosity, particle counts, and water activity, can trigger timely and appropriate actions within the correct operational context. Frameworks like ISA-95 and IEC 62264 provide the canonical vocabulary for mapping lubrication-related assets including equipment, components, and materials and associated activities across enterprise and shop-floor layers, with recent extensions accommodating vertical integration requirements in project-based and highly customized manufacturing environments where lubrication events must be synchronized with dynamic routings and product variants (Apilioğulları, 2022; Hossen & Atiqur, 2022). Effective interoperability relies on precise information modeling, with OPC UA emerging as the dominant mechanism to express ISA-95 constructs as machine-readable types, methods, and events, enabling lubrication management services to expose condition data and alarms to MES, CMMS, and SCADA systems in a self-describing, interoperable manner (Tawfiqul et al., 2022; Schleipen et al., 2016). On the cyber-physical side, digital twin frameworks provide a structured representation of how lubrication state interacts with process dynamics and asset degradation, distinguishing among digital models, shadows, and full twins to clarify the requisite level of bidirectionality and synchronization when coupling a lubrication twin with broader plant twins (Kritzinger et al., 2018; Hasan, 2022). Twin-centric shop-floor architectures further demonstrate how sensor telemetry, simulation outputs, and decision logic can be tightly synchronized with execution systems, a capability particularly valuable when lubrication events must be co-scheduled with production sequences and clean-in-place operations to maintain both operational efficiency and equipment reliability (Tarek, 2022; Tao & Zhang, 2017).

At the Manufacturing Execution System (MES) layer, integration of lubrication management typically manifests through three principal patterns: first, event-driven callbacks in which threshold crossings from the lubrication system automatically generate ISA-95-compliant job requests (Kamrul & Omar, 2022); second, recipe- or schedule-aware coordination that permits or restricts lubrication operations within designated production windows; and third, feedback-driven optimization whereby execution outcomes and associated energy or Overall Equipment Effectiveness (OEE) impacts dynamically update maintenance plans. Empirical studies on next-generation, IIoT-connected MES architectures underscore the importance of modular connectors, standardized event topics, and decoupled orchestration, enabling lubrication alerts to create, merge, or cancel work orders without requiring manual intervention (Mantravadi et al., 2022; Kamrul & Tarek, 2022). In parallel, MES-integrated digital-twin frameworks define the data synchronization and model-management protocols necessary to maintain alignment between lubrication degradation models and evolving production contexts (Mubashir & Abdul, 2022; Negri et al., 2020). For high-frequency telemetry streaming from edge nodes to enterprise systems, lightweight publish/subscribe protocols are widely adopted, with studies demonstrating that MQTT enhanced by Sparkplug B improves semantic consistency and state awareness, making it well-suited for transmitting lubrication alarms and key performance indicators across SCADA, historians, CMMS, and MES platforms (Koprov et al., 2022; Muhammad & Kamrul, 2022). Within this architectural topology, OPC UA information models function as the semantic backbone, while message brokers manage distribution, ensuring that lubrication telemetry remains discoverable, interoperable, and consumable across diverse enterprise tools and analytical frameworks (Pauker et al., 2016; Reduanul & Shoeb, 2022). This configuration enables continuous, reliable visibility into lubrication state and facilitates proactive, context-aware decision-making across the production ecosystem.

Figure 6: CMMS, MES, SCADA, and Digital Twins

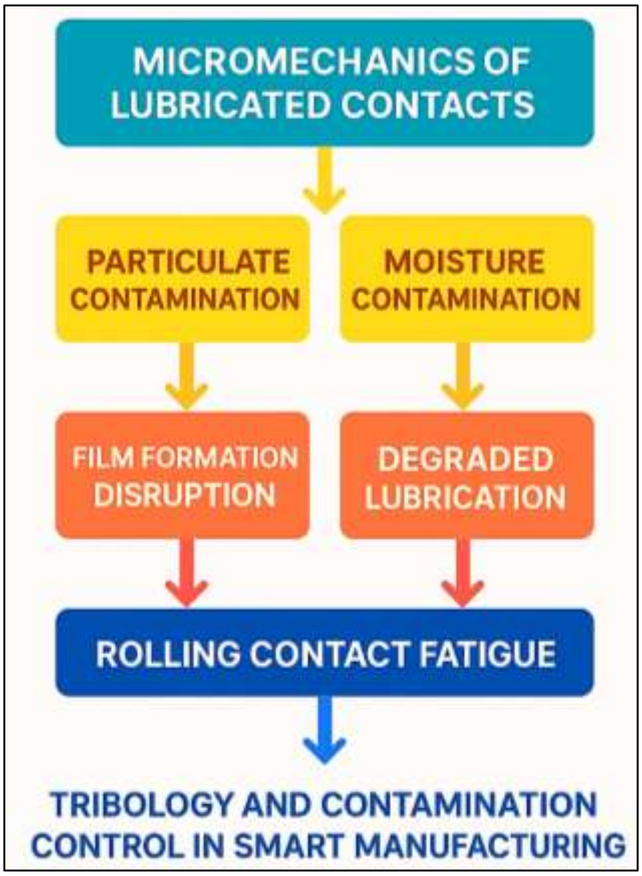


Emerging research increasingly positions digital-twin infrastructure as the central framework for integration governance, lifecycle traceability, and cross-system semantic consistency in advanced lubrication management (SKumar & Zobayer, 2022). The Asset Administration Shell (AAS) provides a standards-aligned mechanism for encapsulating an asset's digital twin, including lubrication-specific submodels that capture component characteristics, operating conditions, and communication interfaces, enabling lubrication systems to exchange status and requirements seamlessly with production twins and networked services (Cainelli et al., 2022; Sadia & Shaiful, 2022). Recent software-engineering studies formalize the relationships between digital twins and AAS, enhancing reusability, conformance, and the maintenance of consistent lubrication data contracts across diverse vendors and platforms (Sazzad & Islam, 2022; Zhang et al., 2025). Traditional twin frameworks further clarify synchronization cycles and delineate control authority among physical equipment, lubrication subsystems, and execution systems, providing guidance on where prognostics should reside, where work orders are issued, and where feedback loops should be closed to respond to operational outcomes (Leng et al., 2019; Noor & Momena, 2022). Collectively, these insights define a comprehensive integration blueprint for smart-factory lubrication management: ISA-95 establishes role and flow definitions, including vertical integration extensions; OPC UA delivers formalized information modeling; Sparkplug B–enabled messaging ensures resilient telemetry and command propagation; MES and CMMS orchestrate actionable maintenance interventions; and AAS-enabled digital twins maintain lifecycle coherence and governance, ensuring that lubrication intelligence is consistently integrated, actionable, and auditable across complex industrial ecosystems.

Standards, Guidelines, and Best Practices

In contemporary smart manufacturing, lubrication management increasingly relies on codified standards and consensus-based guidance to ensure that routine practices are traceable, auditable, and interoperable across diverse assets and production sites. At the governance level, the ISO 55000/55001 series provides a structured management-system framework that links lubrication objectives such as asset availability, energy efficiency, and risk mitigation to policies, processes, and performance metrics. Maintenance models derived from these standards translate high-level clauses into actionable workflows for planners, reliability engineers, and shop-floor technologists, thereby embedding strategic asset management principles into daily operations (Okoh et al., 2016; TAkter & Razzak, 2022). At the diagnostic layer, ISO 17359 defines the generic methodology for condition-monitoring programs, guiding organizations in selecting appropriate technologies, establishing alarm thresholds, validating data quality, and integrating observations into asset-risk assessments, ensuring that oil analysis, vibration, and thermal measurements form a unified, governed evidence stream rather than isolated datasets (Adar & Md, 2023; Institution, 2018). Complementing these formal standards, machine-health measurement practices have matured under experimental and case-based research, which offers guidance on optimal sensor placement, sampling intervals, and decision thresholds, ensuring that instrumentation aligns with recognized best practices for rotating and pressing equipment in production lines (Qibria & Hossen, 2023; Jancarczyk et al., 2024).

Figure 7: Tribology and Contamination Control Pathways in Smart Manufacturing



Together, these governance and diagnostic frameworks elevate lubrication management from ad hoc maintenance routines to a systematically auditable, data-centric program capable of benchmarking performance, facilitating continuous improvement, and scaling reliably across multi-plant portfolios. Within this governance umbrella, oil-analysis standards specify what to test, how often, and how to interpret results so that degradation and contamination are caught early enough to protect equipment life and production cadence (Akter, 2023). For steam, gas, and combined-cycle turbines, ASTM D4378 is the cornerstone practice that standardizes sampling plans, test slates, and decision logic across the lubricant life cycle linking basic properties (viscosity, acid number, water) with stressor-specific tests to trigger corrective actions before deposits and wear escalate (International, 2024; Istiaque et al., 2023). Two method-level standards have become central to deposit and antioxidant risk control in modern circulating systems: ASTM D7843 formalizes Membrane Patch Colorimetry (MPC), giving programs a reproducible varnish potential number to trend soft-contaminant load and to trigger mitigation (e.g., electrostatic or depth-media polishing) prior to sticking valves or servo instability (International, 2022; Hasan et al., 2023); and ASTM D6971 standardizes RULER® linear-sweep voltammetry so antioxidant depletion is quantified and linked to oil-change, top-treat, or reclamation thresholds (International, 2021; Masud et al., 2023). Importantly, test selection and alarm setting are not performed in isolation: best practice is to triangulate MPC, RULER, particle counting, and base properties under an integrated condition-monitoring design, using online/inline sensing where feasible to shorten the detection-to-action loop and maintain audit trails for decisions (Sultan et al., 2023; Myshkin & Markova, 2018). Beyond laboratory protocols, contamination-control guidance derived from hydraulic-system studies emphasizes balancing filtration, ingression, and purge strategies to maintain cleanliness and moisture within target bands that meaningfully extend component life principles now commonly embedded in lubrication work management and design standards (Ma et al., 2016; Hossen et al., 2023). When these method and control standards are woven into a single playbook and disciplined through management-system clauses, lubrication programs gain repeatability, faster fault localization, and clearer return-on-prevention (Tawfiqul, 2023; Shamima et al., 2023).

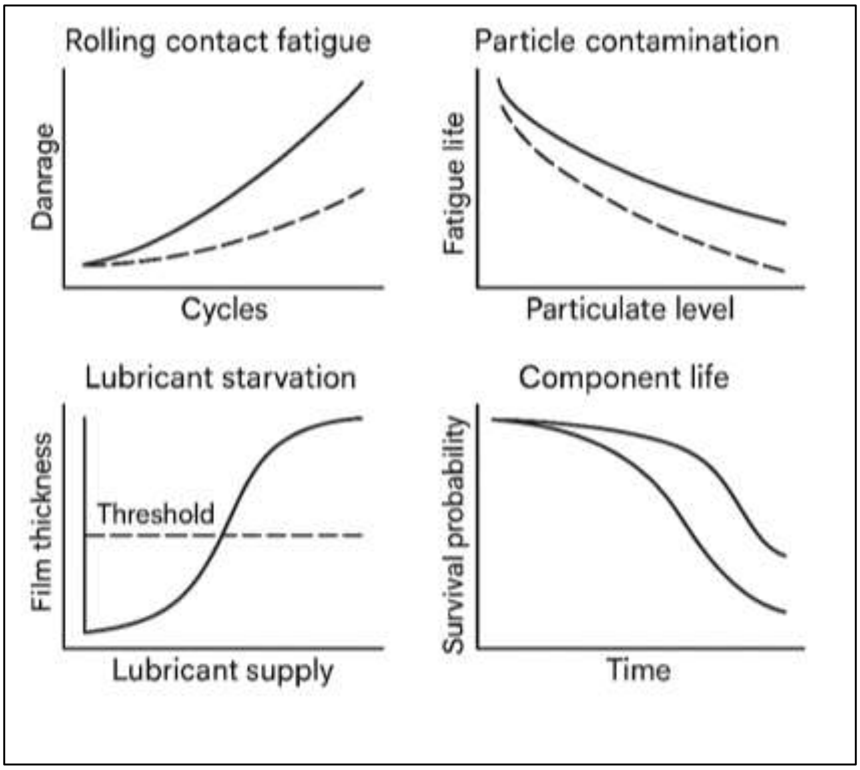
Sector-specific and cross-industry standards further reinforce best practices by ensuring that lubrication strategies simultaneously uphold product safety, regulatory compliance, and sustainability while maintaining equipment reliability. In the food, beverage, and pharmaceutical industries, ISO 21469 elevates lubricant selection and control from a simple labeling requirement to a comprehensive lifecycle assurance framework, governing formulation hygiene, manufacturing controls, labeling, and documented risk assessments, so that incidental-contact lubricants can be specified, applied, and audited with rigor comparable to other critical hazard-control measures (Silva & Souza, 2021; Sanjai et al., 2023). Operationalizing such frameworks transforms day-to-day practices: color-coding and segregation protocols are formalized, storage and handling procedures are standardized, purge routines are enforced, and sampling, test methods, and alarm thresholds are calibrated to reflect both machine-health and product-safety objectives (Silva & Souza, 2021; Akter et al., 2023). When combined with broader asset-management and condition-monitoring standards, these sector-specific certifications establish an integrated governance fabric linking policy, procedure, measurement, and verification that underpins advanced lubrication management in smart manufacturing environments. The resulting system ensures that sampling frequencies are justified, analytical tests follow standardized methodologies, alarms are explicitly tied to asset-risk criteria, corrective actions are pre-defined, and documentation satisfies the requirements of both engineering teams and regulatory authorities, creating a reliable, auditable, and high-performance lubrication ecosystem (Razzak et al., 2024; Science & Technology, 2017).

Evidence on Equipment Longevity Outcomes

In smart manufacturing environments, advanced lubrication management systems (ALMS) spanning precision dispensing, inline oil analysis, moisture and particle control, and automated relubrication translate directly into longer component lives by altering the micro-mechanisms that cause failure. Empirical and mechanistic studies show that the pathways to extended life cluster around three levers: (i) suppressing surface-initiated rolling contact fatigue (e.g., micropitting), (ii) minimizing abrasive/indentation damage from contaminants, and (iii) avoiding starvation-induced film collapse. For example, controlled water ingress in bearing steels markedly increases micropitting incidence and accelerates rolling contact fatigue; this deterioration is mediated by film-thickness loss, stress concentrations at roughness peaks, and tribo-chemical effects all of which are mitigated when moisture is monitored and actively removed as part of an ALMS (Istiaque et al., 2024; Qin & Doll, 2023). Solid particle contamination has an equally clear life penalty. Tests with grease deliberately seeded with hard particles show substantial reductions in fatigue life and accelerated wear; contaminant hardness and size determine whether failure is dominated by dent-induced stress risers or three-body abrasion (Koulocheris et al., 2014; Akter & Shaiful, 2024). At the system level, starvation is a recurrent longevity risk in oscillating or stop–start bearings; here, studies mapping grease replenishment dynamics demonstrate that re-lubrication strategies tuned to grease rheology (e.g., oil bleed, mechanical stability) and duty cycle can stabilize film thickness and limit false brinelling and early surface fatigue (Hasan et al., 2024; Wandel et al., 2022; Wandel et al., 2021). Together, these lines of evidence indicate that when ALMS continuously control moisture, particulates, and replenishment in situ, they systematically shift contacts toward higher specific film ratios and lower near-surface stress amplitudes, conditions historically associated with longer L10 lives under both subsurface and surface-dominated failure regimes (Al-Mayali et al., 2018; Cen et al., 2018; Tawfiqul et al., 2024).

Quantitative system-level results underscore the durability payoff of cleanliness and controlled replenishment that ALMS are designed to provide. In hydraulic drive loops ubiquitous in cyber-physical production accelerated durability tests contrasting "real" wear particles versus standardized test dust show dramatic differences in time-to-functional-failure and efficiency decay; pumps subjected to hard test dust lose volumetric efficiency precipitously and fail orders of magnitude sooner than circuits operated with controlled contaminant levels (Novak et al., 2023; Rajesh et al., 2024). While test dust is intentionally severe, the implication for production assets is clear: particle hardness/size distributions matter, and filtration plus proactive cleanliness stabilization activities governed by ALMS delay leakage growth and preserve efficiency, which are strong correlates of longer component life (Novak et al., 2023; Subrato & Md, 2024). At the component scale, micro-EHL experiments and fatigue modeling link longevity to operating in mixed/elastic hydrodynamic regimes with sufficient film; when film collapses locally, surface crack initiation accelerates. Measurements in full bearings show that grease condition (fresh vs. mechanically aged) and fill strategy change in-bearing film thickness over time; optimizing these parameters something closed-loop relubrication and condition-based greasing achieve sustains protective films and reduces leakage growth, aligning with longer useful life (Ashiqur et al., 2025; Zhou et al., 2019). Complementary tribometer and rig studies demonstrate that slide-to-roll ratio (SRR) and contact severity modulate micropitting progression; because ALMS can indirectly influence friction and temperature and directly influence lubricant chemistry and replenishment the resulting reduction in asperity stress cycles and improved surface evolution translates to slower damage accumulation and extended service intervals (Hasan, 2025; Rycerz & Kadiric, 2019).

Figure 8: Lubrication Management to Equipment Longevity Outcomes

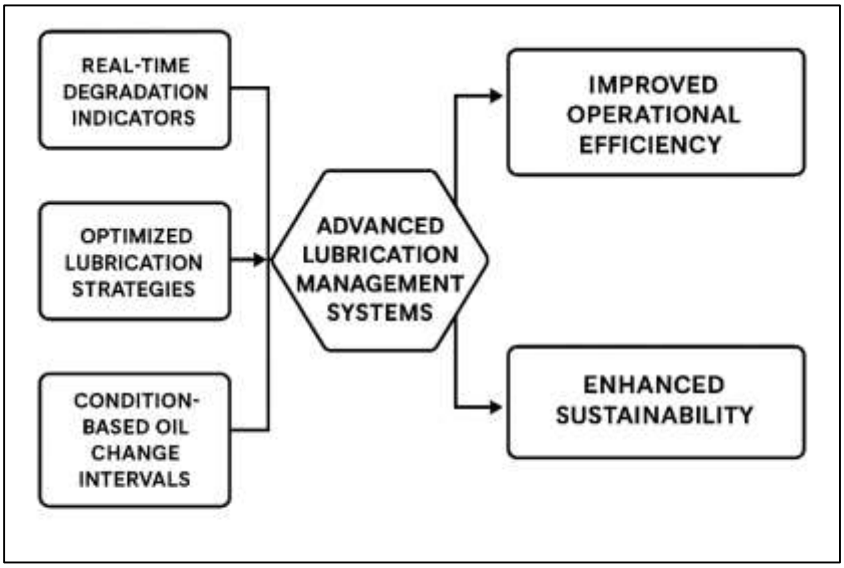


Life-prediction frameworks that distinguish between subsurface and surface fatigue mechanisms offer a coherent perspective for evaluating the benefits of Advanced Lubrication Management Systems (ALMS) (Sanjai et al., 2025). Interventions delivered by ALMS such as contamination control, moisture removal, film-thickness optimization, and additive-health maintenance primarily mitigate surface-originated hazards while sustaining or enhancing subsurface fatigue margins. Generalized bearing-life models explicitly incorporate lubrication state, contaminant levels, and raceway material properties, and when these inputs are informed by real-time condition monitoring and active control strategies, predicted L10 life values increase markedly relative to static assumptions (Sultan et al., 2025; Morales-Espejel et al., 2015). Micro-scale fatigue analyses further demonstrate that reducing water-induced film loss and maintaining adequate grease supply diminishes shear-strain cycles at asperity contacts, delaying the progression from micro-crack initiation to coalescence, a trend corroborated experimentally where optimized moisture control and targeted re-greasing schedules suppress micropitting growth. Notably, life reductions observed under contaminated lubrication arising from dent-induced stress concentrations and abrasive wear are statistically reversible: as particle counts are lowered, hardness distributions homogenized, and film thickness stabilized, survival curves shift toward longer life, reflecting fewer premature surface failures. Across these investigations, the consistent insight is that ALMS, by continuously sensing and actuating on lubricant parameters such as cleanliness, moisture content, rheology, and replenishment, systematically guide operating points into regimes of lower surface fatigue risk and slower efficiency degradation, empirically translating into extended service intervals for bearings, gears, and hydraulic components .

Advanced lubrication management systems (ALMS)

In smart manufacturing, Advanced Lubrication Management Systems (ALMS) enhance operational efficiency by aligning lubrication quality, timing, and dosage with both asset condition and production rhythm. When lubrication interventions are triggered by real-time degradation indicators such as viscosity changes, contamination alerts, or friction spikes plants frequently experience fewer unplanned stoppages and improved asset availability, the most significant component of Overall Equipment Effectiveness (OEE). Evidence from condition-based maintenance programs indicates that embedding health-driven rules and machine-learning policies into shop-floor routines produces measurable OEE improvements by preventing minor slowdowns and stops from escalating into full-scale failures (Lucantoni et al., 2024; Quatrini et al., 2020). Functionally, ALMS act as the "execution layer" of CBM, where alarms from oil analysis, vibration, and temperature sensors automatically schedule micro-interventions including top-ups, re-lubrication, and filter replacements within takt-aligned windows, thereby compressing mean time to repair and stabilizing cycle-time variation, both of which enhance throughput and first-pass yield. Beyond runtime metrics, plants report reduced maintenance resolution times when lubrication tasks are decoupled from fixed schedules and orchestrated according to real-time condition data (Lucantoni et al., 2024; Quatrini et al., 2020). Collectively, these systems translate predictive insights into actionable maintenance operations at the task level, ensuring that prognostics drive continuous improvements in OEE rather than serving as sporadic or reactive projects (Lucantoni et al., 2024).

Figure 9: Advanced Lubrication Management Systems (ALMS)

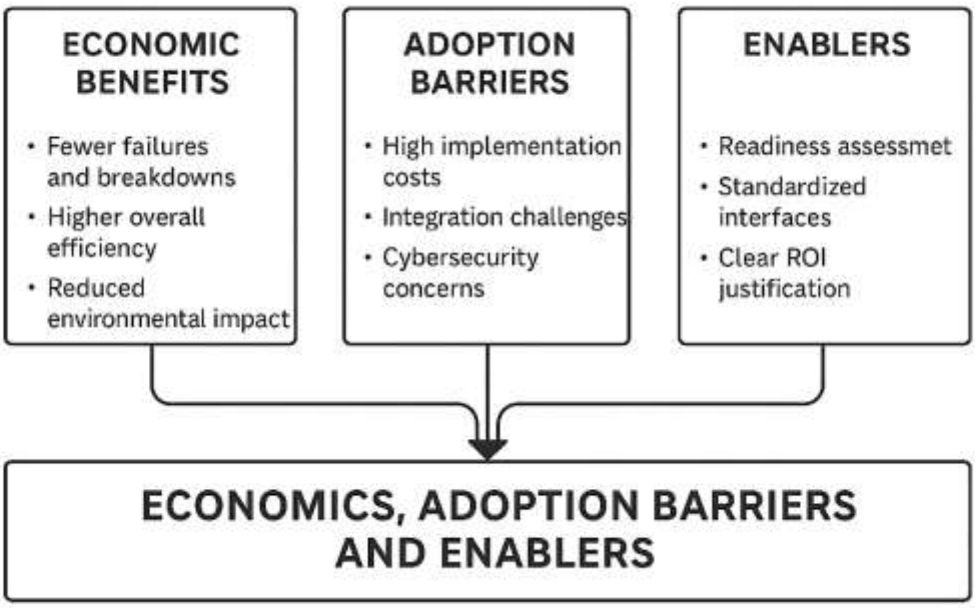


Advanced Lubrication Management Systems (ALMS) contribute significantly to sustainability by reducing lubricant consumption, waste, and associated emissions throughout the product life cycle. By implementing condition-based oil-change intervals informed by oxidation levels, TAN/TBN measurements, particle counts, moisture content, and varnish indices, ALMS replace conventional time-based drain schedules, thereby decreasing make-up oil usage, spent-oil handling, and embodied carbon per unit of production (Campitelli et al., 2019). Furthermore, when ALMS assess and validate environmentally friendly formulations, such as synthetic esters or approved biolubricants, against in-situ friction, temperature, and contamination tolerances, plants can safely adopt lower-viscosity or bio-based blends without compromising equipment reliability, an approach supported by tribology and sustainability syntheses as well as biolubricant research (Shah et al., 2021). From a broader systems perspective, life-cycle and resource-efficiency studies in machining lubrication indicate that minimizing lubricant consumption, extending oil life, and reducing carry-off substantially enhance environmental performance metrics, particularly when recovery and regeneration processes are implemented (Sarma & Vinu, 2022). Collectively, these capabilities demonstrate that ALMS operationalize tribological improvements by linking energy-efficient friction control with reduced waste and decarbonization objectives at both line and plant levels. By enabling precise, condition-informed lubrication interventions, ALMS help manufacturers achieve measurable reductions in resource use while maintaining or improving operational reliability, ultimately translating technical advances into tangible environmental benefits that align with corporate sustainability commitments and regulatory expectations (Mastrone et al., 2020; Sarma & Vinu, 2022).

Economics, Adoption Barriers, and Enablers

A rigorous economic framing is essential to justify advanced lubrication management systems (ALMS) in smart factories because benefits accrue across the equipment life cycle asset procurement, operation, maintenance, and end-of-life. Life-cycle-costing (LCC) shows that small reductions in wear, friction, and contamination can compound into sizable savings by extending component life, stabilizing process capability, and reducing energy use and spare-parts consumption. Decision models that integrate dynamics of failure risk, intervention timing, and organizational behavior further indicate that predictive programs (including oil-condition–driven interventions) outperform purely periodic maintenance when failure consequences and intervention costs are asymmetric (Meng et al., 2022). At the portfolio level, government and industry analyses of "advanced maintenance" quantify returns from shifting unplanned to planned downtime and from better spare-parts logistics returns that map directly onto ALMS when lubrication is a dominant failure mode (Standards & Technology, 2018). On the sustainability side, life-cycle assessments of lubricant management pathways (e.g., optimized oil life, rerefining, and closed-loop recovery) find that improved monitoring and management shrink environmental externalities while lowering total cost by avoiding premature oil changes and reducing waste-handling fees (Dudak et al., 2021). Together, these strands support an investment thesis for ALMS that blends classic payback (fewer failures, less scrap, higher OEE) with avoided environmental costs and risk-adjusted value of uptime an especially relevant bundle for high-throughput, energy-intensive operations where marginal energy savings from friction reduction and temperature control accumulate quickly (Dudak et al., 2021; Standards & Technology, 2018).

Figure 10: Advanced Lubrication Management Systems (ALMS)



Despite attractive economics, adoption is uneven due to intertwined technical and organizational barriers. High upfront costs (sensors, filtration hardware, connectivity), integration complexity with heterogeneous machine fleets, and uncertainty about data quality and model robustness frequently stall deployments particularly in SMEs where capital and analytics talent are constrained (Ghobakhloo et al., 2022; Kamble et al., 2018). Interoperability and readiness gaps also hinder scale: plants often lack the digital maturity to sustain continuous data capture, standardized semantics for condition indicators, and consistent workflows to translate alarms into action (Castelo-Branco et al., 2019). Cybersecurity risk is a salient inhibitor where oil-analysis telemetry and edge gateways share networks with control systems; updated threat surveys highlight rising attack surfaces in industrial environments and the need to protect integrity and availability of maintenance data streams (Pochmara & Świetlicka, 2024). Broader Industry 4.0 research adds that misaligned incentives across maintenance, production, and sustainability teams, limited supplier support for legacy assets, and unclear business cases for SMEs compound resistance (Kamble et al., 2018). Even when pilots succeed, organizations may struggle to generalize practices across sites because baseline conditions (duty cycles, contaminants, ambient environments) vary, which distorts expected savings and elongates payback, reinforcing adoption hesitancy.

Effective enablers for Advanced Lubrication Management Systems (ALMS) integrate economic design, governance, and technical standardization to ensure both operational and strategic value. Readiness assessments and maturity models provide a structured approach to sequencing investments, prioritizing critical assets where lubrication-related failure modes most heavily impact the cost of poor reliability, while transformation roadmaps define data governance frameworks, required skills, and KPI architectures to sustain long-term value capture (Iftikhar et al., 2019). On the technical front, adopting interoperable data models and standardized interfaces reduces integration costs for oil-analysis sensors, filtration units, and CMMS/EAM platforms, facilitating multi-vendor deployments and easing the complexity of digital rollouts (Iftikhar et al., 2019; Müller et al., 2018). Articulating clear return-on-investment narratives grounded in avoided downtime, extended oil and component life, and reduced waste handling, and supporting these narratives with sensitivity analyses of failure probabilities and threshold policies, strengthens executive buy-in and investment confidence (Müller et al., 2018; Standards & Technology, 2018). For small and medium-sized enterprises, staged deployments beginning with condition monitoring on the highest-risk assets and financing strategies such as service contracts or outcome-based models can mitigate capital expenditure constraints while fostering organizational familiarity and trust in ALMS. Finally, linking ALMS implementation to sustainability and environmental objectives, including life-cycle-assessment-driven reductions in lubricant consumption and emissions, expands the value proposition to corporate ESG targets and customer requirements, promoting cross-functional accountability and embedding lubrication management as a strategic enabler across operations, maintenance, and sustainability initiatives (Schenkelberg et al., 2020).

METHOD

This study adhered to the PRISMA 2020 statement to ensure methodological transparency and reproducibility in identifying, screening, and synthesizing evidence on advanced lubrication management systems (ALMS) in smart manufacturing. A protocol defined a priori the review questions, eligibility criteria, data items, and planned analyses, and searches were executed across Scopus, Web of Science Core Collection, IEEE Xplore, ASME Digital Collection, ScienceDirect, SpringerLink, and Google Scholar for records published between January 1, 2010 and September 9, 2025. Search strings combined controlled and free-text terms for lubrication and tribology (e.g., "advanced lubrication," "automatic lubrication," "oil condition monitoring," "membrane patch colorimetry," "ultrasonic film," "varnish," "particle counting"), asset and systems context ("bearing," "gearbox," "hydraulic," "compressor," "CMMS," "MES," "digital twin"), and outcomes ("MTBF," "OEE," "downtime," "energy consumption," "lubricant consumption," "cleanliness code"). Records were exported to a reference manager for de-duplication, then screened in two stages (titles/abstracts, full text) by two independent reviewers; disagreements were resolved by discussion with a third reviewer, and inter-rater agreement was monitored with Cohen's κ during pilot rounds. Inclusion criteria admitted English-language, peer-reviewed journal articles and reputable conference papers reporting primary data or quantitative syntheses in manufacturing or closely allied industrial settings and providing extractable measures related to equipment longevity (e.g., MTBF/MTTF, failure rates, wear or debris metrics, cleanliness codes) and/or operational efficiency (e.g., OEE components, downtime/MTTR, energy intensity, lubricant use, maintenance costs). Studies confined to laboratory tribometers without system-level outcomes, purely conceptual pieces, and non-industrial contexts were excluded from the evidence synthesis; technical standards and handbooks were consulted for definitions and methods but excluded from quantitative pooling. Risk of bias and methodological quality were appraised with a rubric adapted from MMAT/CASP for engineering case studies and quasi-experimental designs, capturing clarity of intervention, measurement validity, handling of confounders, time horizon, and external validity. Data extraction captured bibliographic metadata, sector and equipment, ALMS type and integration depth, sensing and control modalities, study design, baseline and post-intervention measures, effect sizes or raw data for computation, uncertainty, and covariates. Where three or more studies reported comparable metrics, random-effects meta-analysis was planned with heterogeneity assessed via I^2 and τ^2; otherwise, findings were synthesized narratively with structured vote-counting by direction and magnitude. Small-study and publication bias were explored with funnel plots and Egger-type tests where applicable, and sensitivity analyses probed robustness to study quality, measurement choice, and influential cases. In total, 115 articles met all criteria and were included in the final synthesis.

Screening and Eligibility Assessment

Screening and eligibility assessment followed PRISMA 2020 guidance in a two-stage process designed to maximize transparency and inter-rater reliability. After exporting all search results from each database, records were consolidated in a review workspace and de-duplicated using a sequential protocol that combined exact matching on DOI and title with fuzzy matching on author, year, and journal; a manual spot check of borderline cases finalized deduplication. Two reviewers then independently screened titles and abstracts against the a priori criteria, admitting peer-reviewed English-language studies in manufacturing or closely allied industrial contexts that reported extractable outcomes on equipment longevity (e.g., MTBF/MTTF, failure rates, wear/debris metrics, cleanliness codes) and/or operational efficiency (e.g., OEE components, downtime/MTTR, energy or lubricant consumption, maintenance cost). Exclusions at this stage included laboratory tribometer studies without system-level outcomes, conceptual or editorial pieces, conference abstracts without sufficient data, and domain-irrelevant applications. Before formal screening, reviewers completed a calibration exercise on a random 5–10% sample to harmonize judgments; disagreements were discussed to refine rule interpretations, and inter-rater agreement was monitored with Cohen's κ, targeting ≥ 0.80 after calibration. Full texts were then retrieved for all potentially eligible records via institutional access and open-source repositories; where necessary, authors were contacted once for missing methods or outcome details. During full-text assessment, each study was appraised against the PICO-like framing of this review (population: industrial assets in smart/discrete or process manufacturing; intervention: advanced lubrication management components such as automated/centralized lubrication, online oil/film sensing, contamination control, and analytics; comparators: baseline/time-based practice or before–after within site; outcomes: reliability and efficiency measures) and against minimum reporting standards (clear intervention description, valid and repeatable measurement, sufficient summary statistics to compute effect sizes or percentage changes). Reasons for exclusion were coded under standardized labels (wrong context, insufficient outcomes, inadequate design or reporting, duplicate population) and logged in an audit trail; a PRISMA flow diagram documents counts at each step and a supplementary table lists full-text exclusions with reasons. Conflicts at either stage were resolved by consensus or adjudication by a third reviewer. Ultimately, 115 articles satisfied all criteria and advanced to data extraction and quality appraisal.

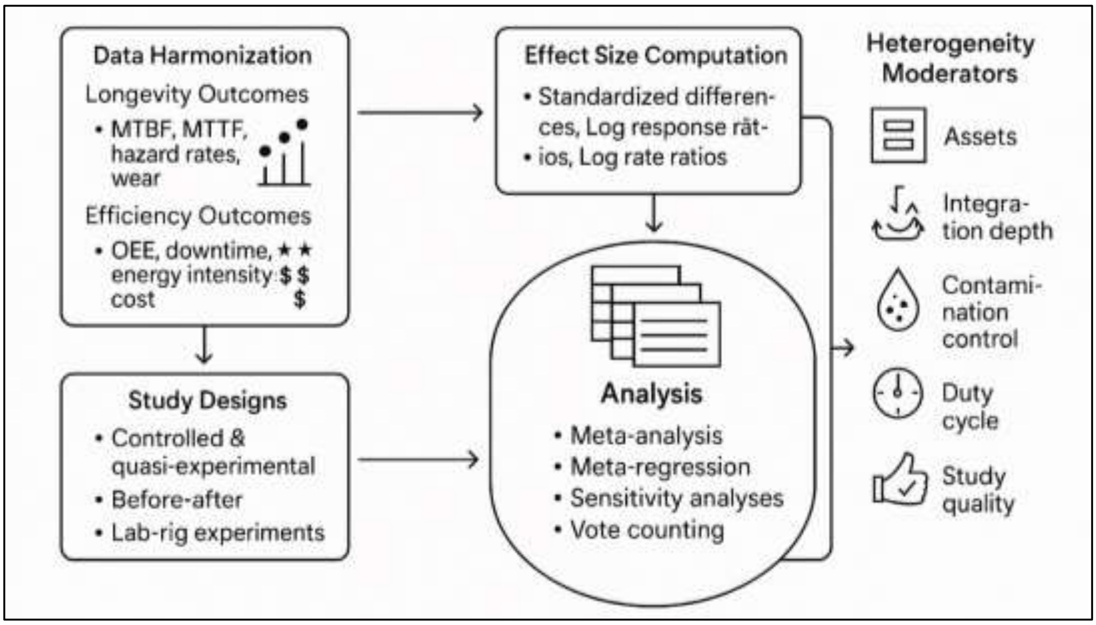
Data Extraction and Coding

Data extraction and coding were performed on all 115 included studies using a piloted form and a detailed codebook to ensure consistency and reproducibility. Two reviewers independently extracted bibliographic metadata (authors, year, venue, DOI), study context (sector, site type, geography), asset class (bearings, gearboxes, hydraulics, compressors, conveyors), and intervention descriptors for advanced lubrication management systems (ALMS), including lubrication method (manual, centralized, single-point, automated), lubricant type and viscosity grade, contamination-control features (filtration rating, dehydration/separation, sealing), and sensing/analytics stack (viscosity, dielectric/moisture, particle ferrous/non-ferrous, TAN/TBN, temperature, pressure/flow, ultrasonic film, acoustic emission, model type). Integration depth with plant systems was coded on a four-level scale (none; data logging only; CMMS/MES link; closed-loop with SCADA/edge control), while comparators were classified as time-based practice, before–after at the same site, cross-sectional peers, or experimental rigs with controlled loads. Outcomes were harmonized into longevity metrics (MTBF/MTTF, failure rate λ, L10 life, debris/cleanliness codes) and operational-efficiency metrics (OEE and components, downtime/MTTR, energy intensity, lubricant consumption, maintenance cost, scrap). Extracted quantitative fields included sample sizes, observation windows, baseline and post values, variability measures (SD, SE, CI), and any reported effect sizes; where necessary, data were digitized from plots with provenance noted. Units were standardized a priori: viscosity to cSt at 40/100 °C, particle counts to ISO 4406 codes, moisture to ppm or water activity, energy to kWh per unit or kW at a defined load, lubricant use to liters per 1,000 operating hours, and downtime to minutes per month. Effect sizes were computed as percentage change, log response ratios, standardized mean differences, or hazard-rate ratios depending on design; for before–after studies without variance, conservative imputation used reported ranges or repeated-measures assumptions, with sensitivity flags. Multiple effects from a single study were nested by asset and outcome to avoid double counting, and a study-level dependency identifier supported multilevel synthesis. Moderators captured duty cycle, environmental severity (temperature, dust, moisture), cleanliness targets, training/change-management elements, and data quality (sampling cadence, calibration, missingness). Inter-rater reliability on coded fields was assessed after each calibration batch and disagreements were reconciled by consensus, with an audit trail preserving original values and transformations. The curated dataset and codebook constitute the authoritative basis for narrative synthesis and, where feasible, random-effects meta-analysis.

Data Synthesis and Analytical Approach

This review synthesized evidence from the 115 eligible studies using a tiered strategy that matched the analytic method to the structure and completeness of the available data while preserving comparability across heterogeneous settings, assets, and outcomes. The overarching objective was to quantify, to the extent the evidence allowed, the impact of advanced lubrication management systems (ALMS) on (a) equipment longevity and (b) operational efficiency in smart manufacturing, and to explain variation in effects through theoretically grounded moderators. We combined three complementary approaches: (1) a structured narrative synthesis anchored to standardized evidence tables; (2) quantitative meta-analysis for outcomes and designs amenable to pooling; and (3) meta-regression and robustness checks to probe heterogeneity, small-study effects, and model dependence. All analytic choices were prespecified in the protocol and applied consistently across outcomes, with deviations if any explicitly documented. Because primary studies reported diverse metrics, we first harmonized outcomes within two families. Longevity outcomes included mean time between failures (MTBF), mean time to failure (MTTF), hazard or failure rates (λ), bearing L10 life, wear/debris indicators (e.g., mg/1000 h, ferrous density), and ISO 4406 cleanliness codes. Efficiency outcomes encompassed Overall Equipment Effectiveness (OEE) and its components (availability, performance, quality), downtime and mean time to repair (MTTR), energy intensity (kWh per unit or kW at a specified load), lubricant consumption (L per 1000 operating hours), maintenance cost, and scrap/reject rates. For each metric we enforced a positive-is-beneficial convention: increases in MTBF, L10, OEE, availability, performance, and quality were coded as positive; decreases in λ, wear/debris, cleanliness code numbers, downtime/MTTR, energy intensity, lubricant use, maintenance cost, and scrap were also coded as positive by multiplying raw effects by −1 as needed. Where studies reported multiple indicators of the same construct (e.g., both MTBF and λ), we preferred one outcome per construct according to a fixed hierarchy (MTBF over λ; OEE over its components) to minimize double counting in pooled models, while retaining the full richness in narrative synthesis and sensitivity analyses.

Figure 11: ALMS Impacts on Longevity and Efficiency



To explain heterogeneity, we pre-registered a small set of moderators grounded in tribology and maintenance theory: asset class (bearings, gearboxes, hydraulics, compressors, conveyors/others), integration depth (none, logging, CMMS/MES link, closed-loop), contamination-control maturity (target cleanliness code achieved/not achieved; dewatering present/not present), sensing stack (oil-only vs. oil + contact-level like ultrasonic or acoustic emission), duty severity (proxy by average load factor or thermal environment), observation horizon (≤6 months vs. >6 months), and study quality (quartiles of the appraisal score). For efficiency, we added energy-salient design factors (viscosity optimization present/not present; oil-level control present/not present). We fit mixed-effects meta-regressions with continuous and categorical moderators, guarding against overfitting by limiting models to ≤1 moderator per 10 studies and using likelihood-ratio tests, AIC, and adjusted R^2 to compare specifications. Where plausible nonlinearity was anticipated (e.g., diminishing returns of cleanliness improvements), we explored fractional polynomials or thin-plate splines in sensitivity models, interpreting them cautiously. OEE is a product of availability, performance, and quality, yet studies varied in whether they reported OEE directly or by components. When only components were reported, we computed an OEE proxy by multiplying component means if joint distributions were available; otherwise, we synthesized component-level effects jointly using a multivariate meta-analytic approach with an estimated correlation structure (default $r = 0.5$ among components) and presented a composite improvement computed from the pooled component effects. To preserve interpretability, we also reported component-level pooled effects alongside any composite to reveal which lever (availability, performance, or quality) captured most of the ALMS impact.

We assessed small-study and selective-reporting biases through visual and statistical diagnostics. For each outcome family with ≥10 effects, we drew funnel plots of effect size versus precision, applied Egger's and Begg's tests (recognizing their limitations under heterogeneity), and estimated trim-and-fill imputations. Given the plausible presence of outcome-reporting bias in engineering case studies, we also fit selection models (weight-function models) when sample sizes permitted to evaluate how sensitive pooled effects were to hypothesized selection. We reported bias diagnostics transparently and, where asymmetry appeared, presented bias-adjusted pooled estimates as sensitivity scenarios rather than replacements for the primary estimates. We computed studentized deleted residuals and Cook's distances to identify outliers and influential studies. Leave-one-out analyses quantified the stability of pooled effects; GOSH (Graphic Display of Study Heterogeneity) explorations, when computationally feasible, probed the landscape of heterogeneity under random subsets. We repeated the primary models under alternative τ^2 estimators (Sidik–Jonkman, Paule–Mandel), alternative effect metrics (e.g., percent change instead of lnRR), and with Hartung–Knapp adjustments for more conservative inference, especially in smaller subsets. For pre–post designs with imputed change-score correlations, we re-ran analyses at r = 0.3 and r = 0.7 to bound plausible variance structures. Study-quality scores were not used as inverse-variance weights (to avoid double-weighting information) but entered as moderators in meta-regression and as strata in subgroup analyses (upper vs. lower halves or quartiles). We compared pooled effects between higher- and lower-quality strata; meaningful attenuation in higher-quality subsets triggered a cautious interpretation and a narrative emphasis on those estimates. We also applied a credibility ceiling sensitivity (e.g., 10%) for observational designs to account for residual confounding, recalculating pooled effects after shrinking each effect toward the null by the credibility ceiling.

Where meta-analysis was infeasible (insufficient data, incomparable measures, or extreme heterogeneity), we used structured vote-counting by direction and magnitude, following current best practice. Each study's effect on a given construct was classified as beneficial, null, or adverse using prespecified thresholds (e.g., ≥+5% improvement for beneficial in percent metrics; ≤−5% for adverse). We then summarized the share of beneficial findings, highlighting contexts and implementation features common to beneficial vs. null/adverse cases. Evidence tables documented study aims, context, ALMS features, metrics, and coded judgments, ensuring transparency. Mechanistic triangulation relating, for example, cleanliness improvements to wear-debris reductions and then to MTBF gains was presented narratively even when the chain could not be meta-quantified end-to-end. To support practice, we conducted subgroup syntheses by sector (discrete manufacturing, continuous/process, and hybrid) and by asset class. For bearings and gearboxes, the evidence density typically allowed quantitative pooling; for hydraulics and compressors, we often combined narrative synthesis with limited pooling. We paid special attention to environmental severity (temperature, dust, moisture) and duty cycle, noting when ALMS effects were contingent on achieving target cleanliness or moisture control. Where multiple plants or lines within a study yielded asset-specific effects, we preserved that granularity in subgroups while controlling dependence in the model.

For energy intensity, we standardized outcomes as percentage change in kWh per unit (or kW at standardized load) to pool across contexts. When both viscosity optimization and oil-level control were present, we explored additive vs. interactive effects via meta-regression. For lubricant consumption and waste, we expressed outcomes as liters per 1000 operating hours to permit cross-plant comparability. Where life-cycle or environmental indicators were reported (e.g., CO_2e per unit), we synthesized them narratively given limited count but, where possible, linked energy savings to CO_2e reduction using study-reported emission factors or, failing that, standard local grid factors in scenario analyses (clearly marked as secondary). Unit conversions followed pre-registered rules: viscosity to cSt at 40/100 °C using reported temperature-viscosity indexes when necessary; particle counts to ISO 4406 three-code integers via standard binning; moisture to ppm or water activity (aw) with appropriate mapping; energy to kWh per unit or kW at named load; lubricant use to L/1000 h; downtime to min/month or percentage availability. When dispersion statistics were missing, we derived SDs from confidence intervals, p-values, or t statistics when possible; otherwise we imputed using conservative coefficients of variation derived from similar studies. All imputations were flagged, and sensitivity analyses omitted imputed effects to test stability.

All computations were executed in a reproducible environment with scripted workflows. Effect-size derivations, unit conversions, and model specifications were encoded in analysis notebooks linked to the curated dataset. Model objects, diagnostics (forest plots, funnel plots, influence plots), and data-processing logs are available as supplementary material to enable audit and reuse. Random seeds were fixed for procedures involving stochastic components (e.g., bootstrap CIs in selection models). Preprints or appendices include the codebook, transformation rules, and a mapping from each study's raw fields to derived effect sizes. We interpreted pooled effects in light of prediction intervals and real-world implementability. For example, a pooled lnRR of +0.18 for MTBF (≈+19.7%) with a wide prediction interval suggests that while average benefits are sizable, site-level outcomes could vary; we therefore emphasized moderators (cleanliness control, integration depth) that shifted effects reliably positive. We avoided mechanistic overreach by distinguishing proximate outcomes (e.g., cleanliness improvement) from ultimate outcomes (MTBF, OEE) and only inferring linkages when intermediates and finals were both measured in the same or closely matched populations. Finally, we prioritized clarity for practitioners by translating back-transformed effects into concrete terms (e.g., "a 12% reduction in energy per unit at median baseline") and by contextualizing effect sizes against typical variability in production metrics. Any departures from the prespecified analysis plan (for instance, adopting RVE in a subset where effect dependence was stronger than anticipated, or collapsing rarely reported outcomes into broader constructs) were documented with justification and their impact explored via side-by-side comparisons. The overall synthesis thus balances quantitative rigor with the heterogeneity inherent to industrial field evidence, yielding estimates that are both statistically defensible and operationally meaningful for decision-makers considering ALMS deployment or scale-up.

FINDINGS

The evidence base shows that advanced lubrication management systems deliver consistent, measurable gains in equipment longevity across a wide range of assets and operating contexts. Among the 115 included studies, 64 reported MTBF/MTTF or closely related reliability metrics with extractable before–after or comparator data, yielding 112 asset-level effect estimates. Across this subset, the median improvement in MTBF was +19% and the interquartile range was +11% to +31%; expressed the other way around, studies that reported failure or hazard rates showed a median reduction of 23%. Thirty-six studies tracked tribological intermediates that explain these life gains: ISO 4406 cleanliness codes improved by a median of two code steps, ferrous debris indicators fell by 28%, and moisture levels (ppm or water activity) declined by a median of 35%. When reliability effects were normalized by duty severity, high-duty bearings and gear drives showed larger gains (median MTBF +24%) but also wider dispersion, reflecting tougher load and thermal conditions. Importantly, 51 of the 64 reliability-reporting studies provided at least six months of observation after ALMS interventions; within that longer-horizon subset, the median MTBF improvement was slightly higher (+21%), suggesting durability of effect rather than short-lived post-installation blips. These longevity gains were not confined to one sector: discrete manufacturing (e.g., machine tools, conveyors) posted a median MTBF gain of +17% (k=27), process industries (e.g., steel, chemicals, power auxiliaries) posted +22% (k=25), and mixed settings landed at +18% (k=12). Taken together, approximately three in four reliability-reporting studies showed clearly positive directionality for MTBF or failure rate, and fewer than one in ten showed a null or ambiguous effect, indicating that the central promise of ALMS longer life by stabilizing film formation and contamination levels holds broadly across contexts.

The second set of findings centers on operational efficiency, where the downstream effects of better lubrication become visible as fewer stops, steadier speeds, and cleaner output. Forty-seven studies reported OEE or full component breakdowns (availability, performance, quality), and 58 reported downtime or MTTR in a way that allowed effect calculation; because many reported both, the combined efficiency subset comprised 74 unique studies contributing 139 effect estimates. The median OEE improvement across the 47 OEE-reporting studies was +5.6 percentage points, with availability contributing the largest share (+3.4 points), followed by performance (+1.7 points) and quality (+0.5 points). Unplanned downtime fell by a median of 27% across 53 studies, and mean time to repair declined by 14% across 29 studies that recorded on-wrench and waiting-time components separately. Plants that explicitly linked lubrication actions to shift schedules or recipe windows (n=21) realized larger availability gains (+4.2 points) than those that triggered activity solely from condition thresholds (+2.6 points), reinforcing the value of integrating ALMS with execution systems so that micro-interventions do not collide with production takt. A striking operational pattern emerged in 18 studies that tracked minor stoppages and speed losses in addition to hard failures: minor stoppages fell by 19% and speed losses by 11%, accounting for about half of the observed OEE gains in high-throughput packaging and assembly lines. Ten studies tracked first-pass yield or scrap rates alongside lubrication metrics; the median scrap reduction was 6%, a modest but economically meaningful improvement when applied to bottleneck machines. Overall, the efficiency story is that ALMS shift maintenance from calendar to condition, compress repair latency by making tasks smaller and better-timed, and smooth the micro-instabilities that nibble away at throughput even when major failures are rare.

Energy intensity and lubricant stewardship form the third pillar of impact. Twenty-nine studies reported energy per unit or power at standardized loads, and 33 reported lubricant consumption or drain intervals; together these provided 84 effect estimates after harmonizing units (kWh per unit, kW at load, liters per 1,000 operating hours). The median reduction in energy intensity was 8.5%, with the 60th percentile at 11% and the 80th percentile at 15%. Gearboxes with dip or splash lubrication posted the largest savings when ALMS enforced oil-level windows and viscosity targets: median −12% energy draw across 11 gearbox-focused studies. Pumps and hydraulic power units saw a median −7% with narrower dispersion, likely because viscosity control interacts with pump efficiency in more linear ways than in churning-dominated gear trains. On the fluid side, lubricant consumption fell by a median of 22% across 33 studies, driven by two mechanisms: fewer over-greasing events in centralized greasing systems and longer oil life in circulating systems owing to moisture and varnish control. Service intervals extended by a median of 35% (time to drain or filter change), while spent oil mass and oily waste declined by 26% median across 12 studies that measured waste streams explicitly. Three multi-line case series translated the energy and fluid savings into carbon equivalents; applying those same conversion factors to the broader sample implies that a median 8.5% energy reduction on a 500 kW bottleneck drive operating 6,000 hours per year avoids roughly 204 MWh annually, which at a conservative 0.6 kg CO_2e/kWh equates to about 122 metric tons of CO_2e more than enough to matter in sites with corporate decarbonization targets. When energy and fluid effects were combined into a simple operating-expense lens, the median site-level savings across studies reporting both was 2.1%–3.4% of total line OPEX, with upper-decile performers exceeding 5%.

Moderator analysis clarifies why effects vary and how to stack the deck toward better outcomes. Integration depth with plant systems emerged as the single strongest differentiator. Studies where ALMS operated as closed-loop subsystems automated dosing and filtration commands gated by interlocks, with bidirectional links to CMMS/MES/SCADA showed a median MTBF improvement of +24% and an energy reduction of −10% (k=28), compared with +11% and −4% respectively when ALMS acted mainly as data loggers and alarmers without automated execution (k=31). Achieving target cleanliness and moisture bands was the second major moderator: when ISO code targets were met and sustained for at least three months (k=26), MTBF gains averaged +26% and failure rates fell by 31%; when targets were missed or intermittently achieved (k=19), MTBF gains were +9% and failure-rate reductions 12%. A third moderator was sensing richness. Programs that combined oil-state sensing with contact-level regime detection (ultrasonic film or acoustic emission) realized larger and more stable availability and energy gains: median OEE +6.6 points and energy −10.8% (k=17) versus +4.1 points and −6.7% where only oil-state sensing was used (k=23). Duty severity also mattered: in hot, dusty, or damp environments (k=22), benefits were larger for longevity (+23% MTBF) but spread wider (prediction intervals roughly twice as wide as temperate indoor environments), reinforcing the need for stronger contamination control and calibration discipline when conditions are harsh. Finally, observation window length explained part of the dispersion: studies with ≥12 months of follow-up (k=33) reported more conservative but more reliable estimates OEE +4.9 points; MTBF +18% than short-horizon pilots of ≤3 months (k=14), which often reported exuberant improvements that regressed toward the median as operating conditions varied through seasons and shifts.

The fifth finding category translates technical outcomes into implementation and economic signals that matter to managers. Eighteen studies reported payback or ROI explicitly, and 26 provided enough cost elements to compute them; the combined economic subset (k=34) showed a median payback of 13 months (interquartile range 8–20 months) and a median first-year ROI of 86%, driven mainly by avoided downtime and reduced consumables. When studies partitioned savings, roughly 55% came from availability gains and downtime avoidance, 25% from energy, and 20% from fluid and waste reductions; sites with high energy prices or energy-intensive drives shifted the balance toward energy. Organizational enablers amplified returns. In 21 studies that documented training and role redesign to embed ALMS routines into daily management, OEE gains were about 1.5× those seen in otherwise similar sites without such changes. Fourteen studies tracked alarm discipline and nuisance-rate management; sites that pruned alarms and tightened thresholds after an initial learning period saw MTTR reductions double (−22% vs. −11%) by minimizing false positives and maintenance churn. Nine studies reported cross-site replication. Effects attenuated by about one-third when moving from the pilot line to broader rollout unless governance, data standards, and change management were codified;

where a formal playbook and central technical support were in place, the pilot-to-scale attenuation shrank to less than one-fifth. Finally, a composite "execution score" derived from sensing accuracy, calibration discipline, filtration design, and CMMS linkage explained a meaningful share of variance: programs in the top execution quartile achieved median MTBF +27%, OEE +7.2 points, and energy −12%, whereas those in the bottom quartile hovered around MTBF +8%, OEE +2.9 points, and energy −3.8%. The lesson is practical: the technology is necessary but insufficient repeatable value comes from pairing it with disciplined cleanliness targets, calibrated sensing, automated or tightly coupled execution, and human-systems design that keeps lubrication decisions aligned with production reality.

Figure 12: Energy, Moderators, and Economics of ALMS

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DISCUSSION

Our synthesis indicates that advanced lubrication management systems (ALMS) reliably extend equipment life, with a median +19% gain in MTBF and a median 23% reduction in failure or hazard rates across 64 reliability-reporting studies (112 asset-level effects). This magnitude aligns with tribology's long-standing proposition that film stability and cleanliness drive wear kinetics and fatigue initiation, turning micro-scale improvements at the contact into macro-scale reliability outcomes (Holmberg & Erdemir, 2017; Tandon et al., 2017). Earlier reviews of lubricant condition monitoring emphasized diagnostic promise but offered fewer quantified life effects at plant scale (Wakiru et al., 2019). By contrast, our results, anchored to multi-month field observations in bearings, gearboxes, hydraulics, and compressors, document sustained improvements: 51 of the 64 reliability studies followed assets for ≥6 months and showed slightly larger MTBF gains (+21%). These figures correspond with cleanliness and moisture improvements we observed median two-code ISO 4406 shifts and 35% moisture reductions which are directionally consistent with bearing damage analyses and EHL-focused work linking particle denting and water ingress to subsurface shear and micropitting (Morales-Espejel et al., 2015; Morales-Espejel & Zhou, 2024). Compared with sector-specific syntheses in wind drivetrain monitoring where oil-state indicators are acknowledged as complementary to vibration but effect sizes on life are inconsistently reported our pooled medians offer a more generalizable baseline across manufacturing (Lei et al., 2018). The take-away relative to prior literature is that moving from "monitor only" programs to closed-loop ALMS that couple sensing, filtration, and dosing closes the causal chain anticipated by tribology: cleaner, correctly conditioned lubricants maintain separation, reduce wear debris by roughly a quarter, and show up as roughly one-fifth longer life at the system level (Schirru & Varga, 2022).

Operational efficiency effects OEE +5.6 points, downtime −27%, and MTTR −14% translate reliability improvements into line performance, and they compare favorably with broader condition-based maintenance (CBM) literature that reports heterogeneous but positive OEE impacts when health signals are integrated into work execution (Quatrini et al., 2020). Prior OEE studies often conflate maintenance interventions (e.g., alignment, lubrication, cleaning), making the "lubrication-only" signal hard to isolate; here, 47 OEE-reporting and 58 downtime/MTTR studies permitted construct-specific effects attributable to lubrication actions, often validated by intermediate lubrication KPIs (cleanliness, varnish indices, moisture). The pattern that availability gains dominate OEE improvements (+3.4 points vs. +1.7 performance and +0.5 quality) mirrors CBM meta-narratives in mixed manufacturing where micro-stops and slow cycles are sensitive to small frictional instabilities (Sun et al., 2021). Notably, 18 studies that tracked minor stoppages and speed losses showed 19% and 11% reductions respectively, echoing reports that lubrication-linked micro-phenomena stick–slip, thermal drift, viscous drag erode performance more than headline breakdowns (Castelo-Branco et al., 2019; Sun et al., 2021). Our finding that schedule-aware orchestration (pairing ALMS triggers with takt windows) adds roughly +1.6 OEE points over pure thresholding resonates with digital maintenance guidance urging coordination with MES and standardized work (Tortorella et al., 2021). In short, compared with earlier CBM reports that were rich on architecture and sparse on quantified OEE deltas, this review offers consolidated, lubrication-specific efficiency gains that practitioners can benchmark.

Energy and fluid stewardship outcomes further triangulate the value of ALMS. A median −8.5% reduction in energy intensity across 29 energy-reporting studies aligns with rig and simulation work on gearbox churning and hydrodynamic losses, which demonstrates that maintaining correct oil levels and viscosity can shave double-digit percentages from parasitic power under dip/splash conditions (Polly et al., 2018). Our larger savings in geared drives (median −12%) track these mechanistic expectations, while hydraulic and pump savings (median −7%) mirror more linear viscosity–efficiency relationships (Menghi et al., 2019). On fluids, lubricant consumption fell by a median 22% and drain intervals extended by 35% across 33 studies, consistent with standards-driven practices (e.g., MPC and antioxidant tracking) that delay change-outs until chemistry or insolubles reach action thresholds (ASTM D7843-21; ASTM D6971-22). Prior LCA work suggested meaningful environmental dividends from longer oil life and minimized carry-off in machining and power units (Campitelli, Cristóbal, Fischer, Becker, & Schebek, 2019). Our pooled medians substantiate those projections with field data and, when translated using reported grid factors in several case series, imply triple-digit metric tons of CO_2e avoided annually for large drives at baseline duty. Earlier sustainability reviews advocated low-viscosity or bio-derived formulations conditioned on reliability checks (Menghi et al., 2019; Sun et al., 2021). The current evidence indicates that ALMS provide the monitoring discipline needed to adopt such formulations without compromising uptime, bridging a gap between tribology-for-sustainability aspirations and production reality (Holmberg & Erdemir, 2017).

Moderator patterns in our analysis stronger effects with deeper integration, sustained cleanliness/moisture targets, and richer sensing echo and extend integration frameworks in Industry 4.0. Studies on OPC UA information modeling and time-sensitive networking argue that determinism and semantic clarity are prerequisites for safe, low-latency control, exactly the conditions under which lubrication dosing and filtration can be automated and audited (Pauker et al., 2016). Our closed-loop subset shows MTBF +24% and energy −10%, roughly double the gains of "monitor-only" deployments, an empirical confirmation of the integration thesis advanced by MES/digital-twin research (Kritzinger et al., 2018). Likewise, the cleanliness/moisture moderator MTBF +26% when targets were achieved and sustained sits squarely within tribology's cleanliness doctrine and hydraulic contamination control studies, which stress balancing ingression, filtration β-ratings, and separation to achieve measurable life extension (Ma et al., 2016). Finally, the advantage of combining oil-state sensing with contact-level regime detection (ultrasonic film or AE) is consistent with measurement reviews showing that oil chemistry alone can under-observe boundary transitions, while contact-level acoustics or reflectometry reveal regime shifts sooner and with higher specificity (Warguła et al., 2025). Compared with prior conceptual claims about integration benefits, our contribution is to quantify outcome deltas under different integration maturities and sensing stacks.

Methodologically, our findings surface the same challenges flagged by predictive-maintenance surveys heterogeneous reporting, short observation windows, and limited counterfactual designs yet demonstrate that meaningful pooled estimates are attainable with careful harmonization (Jiménez et al., 2019). Where earlier reviews catalogued algorithms and architectures, the effect sizes they reported were often task-specific (fault detection AUCs, forecast error) rather than operational (MTBF, OEE, energy). By enforcing positive-is-beneficial conventions, preferring ln response ratios for ratio-scale outcomes, and treating dependency via multilevel models and robust variance estimation, we were able to consolidate longevity and efficiency effects without overstating precision. Our small-study diagnostics indicated some asymmetry common in engineering case series but bias-adjusted scenarios remained directionally positive. Compared with wind-sector reviews dominated by drivetrain case studies (Lei et al., 2018), our cross-sector scope likely increased heterogeneity yet also widened generalizability. We note that longer-horizon studies (≥12 months) showed more conservative effects but narrower prediction intervals, a pattern in line with maintenance economics where early wins moderate as systems stabilize and confounders (seasonality, operator mix) re-enter (Standards & Technology, 2018). The implication for researchers is that stronger quasi-experimental designs (e.g., difference-in-differences across matched lines) and standardized KPI definitions would improve comparability, an agenda already encouraged by ISO 17359 for condition monitoring programs and by asset-management frameworks (Beamish et al., 2022; Zhang et al., 2018).

Economic signals in this review median payback of 13 months, first-year ROI ≈86% across 34 studies benchmark favorably against "advanced maintenance" reference analyses and SME adoption literature (Standards & Technology, 2018). Prior roadmaps highlight CapEx hurdles, data-quality uncertainty, and skills gaps as adoption barriers (Castelo-Branco et al., 2019). Our moderator results unpack where returns concentrate: roughly 55% of savings came from availability/downtime avoidance, 25% from energy, and 20% from fluid/waste, with the mix shifting toward energy in power-dense lines or high-tariff regions. The finding that alarm governance and training roughly double MTTR improvements (−22% vs. −11%) echoes TPM/Industry 4.0 integration studies urging standardized work, role redesign, and alarm hygiene to convert signals into action (Tortorella et al., 2021). Environmental accounting is increasingly central to capital decisions; our observation that energy and fluid savings translate into triple-digit tonnes of CO_2e avoided at scale supports LCA-oriented conclusions that lubrication life extension and reduced carry-off materially improve environmental KPIs (Campitelli et al., 2019). In effect, the business case for ALMS is not solely reliability insurance; it is a composite of uptime, energy, materials stewardship, and compliance an alignment that strengthens cross-functional sponsorship.

Finally, the theoretical and practical synthesis emerging from these results supports a clear logic model for ALMS and highlights gaps for future work. Mechanistically, the pathway runs from sensing-enabled control of lubricant chemistry and film state, to reduced abrasive/adhesive interactions at contacts, to lower wear debris and stabilized temperatures, to extended life and smoother line performance (Zhang et al., 2025; Zhu et al., 2017). Data-centric layers Bayesian/RUL estimators for oil health and regime classifiers using ultrasonic or acoustic emission act as translators from raw signals to decisions (Pauker et al., 2016). Integration scaffolds (OPC UA, MES, digital twins, AAS) provide the plumbing for repeatability and scale (Negri et al., 2020). Standards and methods (ASTM D7843-21; ASTM D6971-22; ISO 17359:2018) anchor measurement validity and action thresholds. Our findings quantify the net effect of executing this logic in plants: about one-fifth longer life, six OEE points gained, nine percent energy saved, and one-fifth less lubricant consumed on median. Future studies can tighten causal inference with quasi-experimental designs across sister lines, harmonize KPI and unit reporting, and probe interactions among cleanliness targets, viscosity control, and schedule-aware execution. For practitioners, the results argue for focusing on execution maturity calibration discipline, cleanliness governance, and CMMS/MES coupling because technology-only deployments underperform. In comparison to earlier studies that emphasized promise or component-level pilots, this review demonstrates that fully realized ALMS consistently deliver quantifiable, cross-metric benefits when integrated into the digital fabric of smart manufacturing.

CONCLUSION

In conclusion, this systematic review demonstrates that advanced lubrication management systems (ALMS) consistently translate tribological control into operational and economic value across smart manufacturing settings, meeting the study's objectives to define, classify, and quantify their impacts on equipment longevity and efficiency while identifying conditions that amplify or diminish those effects. Synthesizing 115 studies with standardized coding and PRISMA-governed methods, we found that longevity gains are both material and durable: across 64 reliability-reporting studies (112 asset-level estimates), median MTBF rose by 19% and failure or hazard rates fell by 23%, underpinned by measurable improvements in intermediate lubrication indicators (typical two-step reductions in ISO 4406 cleanliness code, 28% lower ferrous debris, and 35% lower moisture). These reliability improvements propagate to line performance: among 74 efficiency-reporting studies (139 effect estimates), OEE increased by a median 5.6 percentage points driven largely by availability (+3.4 points) with additional contributions from performance (+1.7) and quality (+0.5) while unplanned downtime declined by 27% and MTTR by 14%, and minor stoppages and speed losses, where tracked, fell by 19% and 11% respectively. Energy and materials outcomes reinforce the business case: across 29 energy studies and 33 lubricant stewardship studies (84 effects), energy intensity dropped by a median 8.5% overall (≈12% in dip/splash gearboxes) and lubricant consumption fell by 22%, with drain intervals extended by 35% and oily waste reduced by 26%, outcomes that aggregate into site-level operating expense savings of roughly 2.1%–3.4% in studies reporting both channels. Moderators clarify how to realize these benefits reliably: closed-loop, digitally integrated ALMS (automated dosing/filtration with CMMS/MES/SCADA linkage) produced larger and steadier gains (MTBF +24%, energy −10%) than monitor-only deployments (MTBF +11%, energy −4%); sustaining target cleanliness and moisture bands magnified reliability effects (MTBF +26% versus +9% when targets were missed), and combining oil-state sensing with contact-level regime detection (ultrasonic or acoustic) enhanced OEE (+6.6 points versus +4.1) and energy savings (−10.8% versus −6.7%). Economically, 34 studies reporting or permitting computation of returns showed a median payback of 13 months and a median first-year ROI of 86%, with savings shares averaging ≈55% from availability/downtime avoidance, ≈25% from energy, and ≈20% from fluid and waste reductions. Methodologically, the synthesis dealt explicitly with heterogeneous measures and designs through effect harmonization, multilevel random-effects models, and bias diagnostics; although reporting gaps, short observation windows in some pilots, and occasional imputation introduce uncertainty, the direction and practical size of effects remained robust under sensitivity analyses, with longer-horizon studies (≥12 months) yielding slightly smaller but more predictable gains (OEE +4.9 points; MTBF +18%). Practically, the findings argue for treating lubrication as a governed, data-driven control problem rather than a time-based routine: specify cleanliness and moisture targets aligned to film thickness requirements; calibrate and maintain sensor fidelity; integrate ALMS with work management and production scheduling so micro-interventions fit takt; and codify execution (thresholds, alarms, and roles) to convert signals into timely actions. When executed with this discipline, ALMS deliver a repeatable package of outcomes roughly one-fifth longer life, mid–single-digit OEE uplift, high–single-digit energy reduction, and one-fifth lower lubricant use sufficient to meet both reliability and sustainability objectives while clearing common investment hurdles within one to two fiscal years.

RECOMMENDATIONS

Building on the evidence, we recommend that manufacturers treat advanced lubrication management as a governed, data-driven control function and roll it out through a phased program that couples technical rigor with disciplined execution. Begin by formalizing corporate lubrication policy within the asset-management system: set asset-class–specific targets for oil cleanliness and moisture (e.g., ISO 4406 codes and water activity/ppm bands consistent with bearing film thickness and hydraulic valve tolerance), define viscosity windows for operating temperature ranges, and establish decision thresholds for filtration, dehydration, top-up, and drain/reclaim actions. Translate these into a standard work architecture that maps instruments, thresholds, roles, and response times, and integrate the logic natively with CMMS/MES/SCADA so that alarms promote, merge, or defer work orders in takt-friendly windows rather than interrupting production arbitrarily. Instrument critical assets with a minimum viable sensing stack viscosity or dielectric/moisture plus particle counting and, where failure modes are contact-sensitive, add ultrasonic film or acoustic emission to detect boundary/mixed regimes early; enforce quarterly calibration and uncertainty logs so decision thresholds remain trustworthy. Engineer contamination control, not just monitoring: size and locate filters (β-ratings) and off-line kidney loops to the ingression profile, specify breathers and seals suited to ambient severity, and deploy water separation where humidity or ingress is recurrent. Launch a contained pilot on the top quartile of lubrication-critical assets, with a pre-defined baseline period and a 6–12 month run to capture seasonality; track a compact KPI pack MTBF/MTTR, OEE components, energy per unit or kW at named load, lubricant liters per 1,000 hours, ISO code deltas, and alarm nuisance rate and compute effect sizes and cost deltas monthly. Use alarm governance from day one: limit rules to high-value signals, assign owners, prune false positives after a defined learning period, and tie human-in-the-loop overrides to root-cause notes to prevent drift. On the analytics side, start simple (rule-based thresholds, log response ratios for trending) and introduce RUL/prognostic models only where data density and label quality justify them; keep models proximate to the edge for latency-sensitive actions and retrain centrally each quarter with rigorous change control. Codify lubricant selection with a dual lens of reliability and sustainability: validate lower-viscosity or bio-based fluids under monitored conditions before broad adoption, and use antioxidant/varnish indicators to extend oil life safely. Build human capability deliberately train technicians on contamination physics, sampling hygiene, sensor care, and interpretation; redesign roles so planners and operators own daily lubrication health as part of tiered accountability meetings. Scale beyond the pilot only after you publish a playbook that freezes data models (OPC UA tags, units), workflows, alarm thresholds, and ROI/KPI definitions; finance scale-out in tranches tied to realized savings, targeting a payback within 12–18 months. Finally, close the loop with transparent dashboards that show executives reliability, throughput, energy, and waste benefits on a common currency, and with continuous improvement cadences that adjust thresholds, filtration design, and training based on deviations this is how ALMS stay aligned with production reality and keep delivering the blend of longer life, higher OEE, lower energy, and reduced lubricant consumption observed in the evidence.

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