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Sensor-Efficient Health Monitoring for Brownfield Industrial Hydraulic Systems

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Abstract.

SMS group GmbH presents a hierarchical health tree condition monitoring system specifically engineered for brownfield industrial hydraulic installations, where brownfield installations refers to the process of upgrading, expanding, or re-purposing existing facilities, for example by integrating online monitoring technologies or modern control systems. Based on SMS group's long-term OEM and service experience in the metal industry, this paper presents a framework to encode expert knowledge into an automated monitoring architecture that avoids the extensive labelled datasets required by many machine-learning approaches. The framework aggregates sensor data and operational parameters into a single, transparent Health Index, providing intuitive, real-time feedback for both maintenance and production crews. A novel, aggressive multiplication logic ensures that any component degradation is immediately reflected at the system level, preventing the failure-masking effects of conventional aggregation schemes.

The solution was developed and validated on a 1970s-era rolling mill, designed by SMS group GmbH. The implementation required only a minimal set of strategically placed sensors and a few hours of planned downtime for installation. The results confirm robust fault detection under realistic industrial conditions, thus leading to a significant reduction in unplanned downtime and a significant resource efficiency improvement. Furthermore, the system is able to quantify gradual degradation trends - a practical foundation for future predictive maintenance programs in challenging brownfield environments.

Keywords. Condition Monitoring, Brownfield equipment, Industrial Hydraulics, Health Index, Expert Knowledge, Predictive Maintenance.

1. INTRODUCTION

Complex servo-hydraulic systems have been installed widely in rolling mills since the early 1970s to control the rolling force respectively the roll gap among other functions. With the demand for higher product quality and output, an increasing number of hydraulic functions were introduced into rolling mills, many of which were retrofitted into existing plants. This longevity, however, creates a fundamental tension: while the core machinery endures for decades, its components—comprised of countless moving parts—are inherently subject to continuous wear.

To increase overall equipment effectiveness (OEE) and product quality, a well-maintained hydraulic system is key. The above-mentioned brownfield hydraulic systems, which have grown organically over decades, present a formidable challenge for modernization. They are complex, hydraulically coupled networks of components from various eras, operating under immense pressure to maintain non-stop production.

This research builds upon an SMS group GmbH patent titled 'Method for monitoring the condition of a hydraulic system of a metal forming plant and condition-monitoring device' [1]. The scientific and technical realization of this patented concept was driven by a unique trilateral collaboration: SMS group GmbH, as the original equipment manufacturer (OEM) with decades of service experience, providing the foundational equipment know-how and an operator of a brownfield SMS plant contributing the critical perspective on real-world customer needs. This combined industrial expertise was then scientifically processed by the Chair of Fluid-Mechatronic Systems (TU Dresden), allowing to develop the methodology and implementation described in chapter 4 and following.

The central question this work addresses is how to bridge the gap between sophisticated maintenance experience and the need for digital, systematic monitoring in an environment where resources are severely constrained. Our answer is rooted in the formalization of decades of hands-on experience from maintenance and commissioning experts within the SMS group GmbH. This deep, practical knowledge is the essential ingredient to translate the complex, often tacit, operational experience from a customer's production environment into a systematic, digital assessment. Prevailing condition monitoring paradigms often prove unsuitable for this context. Approaches rooted in machine learning and artificial intelligence frequently require vast amounts of labelled fault data. This prerequisite fundamentally clashes with the reality of economically viable brownfield systems for two reasons: first, fault states are by necessity rare, making such data inherently scarce; second, their root causes are often obscured by complex system-level interactions that defy simple generalization. This data scarcity and ambiguity often result in “black box” models that are met with distrust by experienced maintenance crews [2]. While valuable for algorithmic development, solutions demonstrated on laboratory test rigs under controlled conditions often fail to translate to the operational volatility of a real factory floor.

Indeed, sophisticated approaches like hierarchical health index frameworks have been successfully implemented in data-rich sectors like semiconductor manufacturing [3]. However, these successes are typically enabled by extensive sensor networks and dedicated data science teams capable of managing complex statistical aggregation methods, such as the Analytic Hierarchy Process (AHP). This creates an economic and logistical barrier that is insurmountable for most legacy brownfield plants. Furthermore, these methods often involve complex weighting debates and can mask critical single point degradations through averaging.

As the SMS group GmbH, we are proud to introduce an elegant approach to implement condition monitoring for existing hydraulic systems: a hierarchical framework designed specifically for resource-constrained, expert-driven environments in brownfield applications of the SMS group GmbH. With this method, we are able to elevate operation of old plants to a new level of availability. For the rolling mill, a reliable operation of the hydraulic system is of absolute importance. Therefore, this paper describes the approach to assessing "Operational Production Health" rather than monitoring single component wear. An 80% worn pump, for example, may still provide 100% production health if it reliably meets the system's current operational demands. Our methodology enables the direct encoding of decades of maintenance expertise into intuitive, transparent operational boundaries. Through a principle of aggressive bottom-up multiplication, any deviation from these expert-defined boundaries at the lowest level immediately impacts the overall system health score. This deliberate choice prevents the masking effects common in weighted aggregation schemes [3], where a single critical failure can be statistically obscured by a majority of healthy components. By ensuring that one bad item "pulls down" the entire branch, we allow the operator to view the tree in a folded state without fear of missing a hidden fault, thereby reducing cognitive overload and allowing for focused troubleshooting only when necessary.

For a more detailed evaluation of the machine condition, the system can also provide further data on individual component wear. This is important for maintenance planning and will be further developed and described in future publications.

This work presents the design, implementation, and results of this framework on a 1970s-era rolling mill hydraulic system. We demonstrate that with the strategic addition of only a few sensors, a comprehensive, scalable, and trustworthy condition monitoring system can be built. The primary contributions are:

- A methodology for capturing and digitalizing expert knowledge without programming.
- A hierarchical aggregation model based on multiplication that ensures transparency and prevents failure masking.
- A clear distinction between component wear and production health, tailored for brownfield systems.
- A practical, module-by-module implementation strategy that minimizes risk and investment.

The following sections will detail the state of the art, present the methodology, describe its implementation and results, and discuss the implications of this approach for the sustainable operation of aging industrial assets.

2. State of the Art and Related Work

The field of condition monitoring is vast, but its application to brownfield hydraulic systems require navigating a specific set of challenges. Following established taxonomies, monitoring approaches can be broadly categorized as model-based, signal-based (including data-driven methods), and knowledge-based. The existing literature can be reviewed through this lens to highlight the specific gap our work addresses.

2.1. Data-Driven and Model-Based Approaches

Condition monitoring approaches are often categorized as either model-based, requiring deep system knowledge, or data-driven, relying on historical process data [4]. Data-driven condition monitoring, particularly using machine learning, represents the most active area of research. The typical workflow involves detecting anomalies, diagnosing their location, and predicting the severity of the damage [5]. However, the success of these methods is critically dependent on the availability of large, comprehensive, and accurately labelled datasets. This prerequisite is a major obstacle in the context of brownfield industrial plants, where historical fault data is sparse or non-existent [6]. Researchers have explicitly acknowledged this “lack of data problem” as a fundamental hurdle, showing that classifiers trained only on simple, single-site damage data struggle to reliably identify more complex, multiple-site fault scenarios [7]. Much of the research is conducted using public benchmark datasets generated on laboratory test rigs, such as the widely used hydraulic system dataset from Helwig et al. [8]. The reviewed study predominantly utilizes machine learning and signal processing techniques. Although effective for pattern recognition, these approaches lack a physical basis, rendering them highly sensitive to noisy or anomalous measurements that may not reflect actual failures or performance degradation.

While invaluable for comparing algorithms, these datasets cannot capture the environmental noise and unique failure modes of a specific industrial installation. More complex “Big Data” frameworks [9], while powerful, assume a level of data velocity and IT infrastructure that is simply not present in the target environment.

Model-based approaches, such as those using Unscented Kalman Filters, offer an alternative by comparing sensor readings to the output of a mathematical system model. They can achieve excellent results in detecting and isolating faults with minimal sensor sets in real industrial machines [10]. However, their primary drawback is the significant upfront effort required to develop an accurate physical model, which is prohibitively complex for an organically grown system with components from different manufacturers and decades of undocumented modifications. Our work positions itself as a hybrid, knowledge-based approach, using data but relying on expert-defined rules rather than statistical models.

2.2. Hierarchical Health Indices

The concept of aggregating multiple sensor inputs into a single, hierarchical health index is an established practice for managing complex assets. Lee et al. developed a comprehensive Equipment Health Index (EHI) framework for the semiconductor industry, which successfully enables real-time monitoring of thousands of machines. It uses a hierarchical equipment structure which relies on statistical process control charts at the leaf level and uses AHP for weighted aggregation. This introduces a layer of statistical complexity and necessitates expert consensus on weighting factors, a process our methodology deliberately avoids.

Similarly, Yuan et al. proposed a Fuzzy Analytic Hierarchy Process (FAHP) to evaluate the health of gas insulated switchgear in power plants [11]. This method also leverages a hierarchical structure and incorporates expert knowledge to define the hierarchy and pairwise comparison matrices. While this validates the use of expert input, it again depends on a complex, weighted aggregation logic that can obscure the impact of a single critical failure and is less intuitive for maintenance personnel without a background in fuzzy logic.

2.3. The Research Gap and Our Contribution

While the literature provides powerful tools for component-specific monitoring and sophisticated frameworks for data-rich environments, a critical gap remains. There is no established methodology that unifies decentralized expert knowledge into a single, transparent system health indicator for brownfield hydraulic systems under severe resource constraints. Existing hierarchical methods rely on complex statistical or weighted aggregations that are ill-suited for production environments where a single failure can halt operations and where trust in the system is paramount.

Furthermore, many data-driven approaches implicitly shift a significant burden onto domain experts: the selection and engineering of relevant features. This is a time-consuming task that experts are often unwilling or unable to perform, creating a bottleneck. Moreover, statistical models are notoriously brittle; their performance degrades when the system's behaviour changes due to modifications or new operational patterns, a common occurrence in brownfield plants, leading to false alarms and a loss of trust.

This paper closes this gap by presenting a framework that is:

1. **Expert-Driven at its Core:** It directly translates operational experience into deterministic rules.

2. **Transparent by Design:** It uses multiplication, avoiding opaque weighting schemes.

3. **Resource-Efficient:** It is built for minimal sensor additions and leverages existing infrastructure.

4. **Pragmatic:** It is scalable and deployable module-by-module without disrupting production.

By doing so, we provide a reproducible template for monitoring the vast number of aging, critical systems that will not be replaced but must be made smarter.

3. METHODOLOGY: THE HEALTH TREE FRAMEWORK

The health tree framework is engineered to overcome the specific challenges of monitoring brownfield industrial systems. The developed methodology rests on three foundational pillars: a deterministic bottom-up aggregation logic that prevents failure masking, a novel interface for capturing expert knowledge without programming, and a hierarchical structure that mirrors the physical plant, eliminating abstract complexity, as shown in Figure 1.

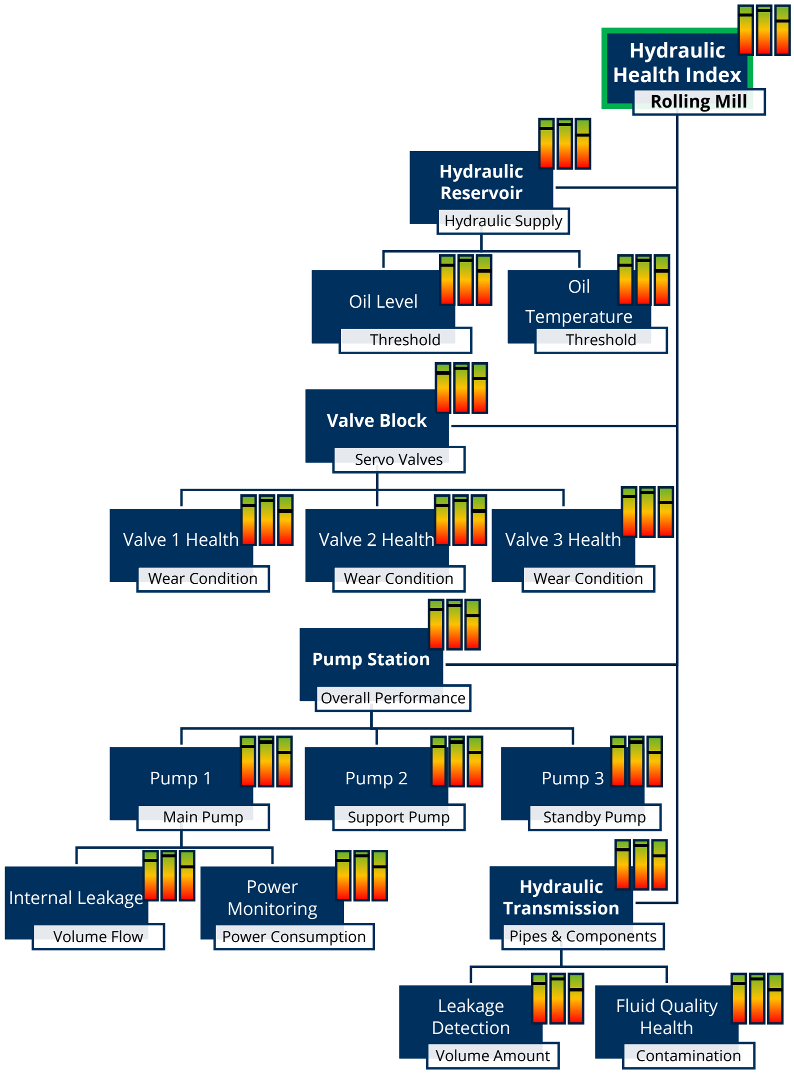

Figure 1 The health tree Framework for the Rolling Mill Hydraulic System (excerpt). This figure shows the root node (Overall System Health Index), branching into major subsystems (Pump Station, etc.), which in turn branch into individual component health indices

3.1. Hierarchical Structure Without Weighting Debates

The framework's main structure, shown in Figure 1, is not an abstract model but a direct digital representation of the physical plant architecture. This hierarchical tree is immediately intuitive to plant personnel who work with the physical system daily.

Level 1 (Leaves): Represent individual sensor inputs or calculated values, each with its expert-defined health function.

Level 2 (Branches): Represent physical components or subsystems, such as a complete pump station or cooling circuit.

Level 3 (Root): Represents the entire hydraulic installation. Its health, the System Health Index (SHI), is the product of all its underlying branches.

Crucially, this structure contains no weighting coefficients. This design choice deliberately eliminates the subjective, political, and often endless debates about whether the pump station is "more important" than the cooling system. The philosophy is absolute: if any single component's condition poses a risk to production, the overall system health must reflect that risk. This deterministic structure ensures that every SHI value is fully traceable. So, any Level 1 harm will be fully recognizable at Level 3 – the SHI.

3.2. Expert Knowledge Capture Without Programming

The core innovation that makes this framework practical is the method for defining the health functions f(s). The challenge was to create a digital representation of the nuanced, often unwritten rules that an expert with decades of experience uses to judge a system's health. To achieve this without requiring any programming skills, the solution was to replace traditional coding with a visual design paradigm. Instead of requiring engineers to write code, we developed an intuitive graphical user interface (GUI) where experts can directly "draw" their experience. The process is simple and powerful:

Graphical Threshold Definition: An expert sketches the acceptable operating region for a parameter directly onto a chart displaying its ranges, comparing it with live or historical data.

Real-Time Visualization: As the expert draws the curve, the resulting mathematical transformation and its effect on the health index are immediately visualized.

Decentralized and Autonomous Work: This tool empowers specialists to work independently. The pump expert defines pump leakage boundaries based on decades of observation, while the cooling systems expert defines temperature limits derived from past summer emergencies.

One-Click Code Generation: Once satisfied, a single click generates the complete, production-ready code for that health function.

This methodology mitigates the persistent challenges of compartmentalized expertise and complex system integration. It provides a structured process to transform valuable, undocumented operational knowledge into a scalable and digital asset, independent of the maintenance staff's programming capabilities.

3.3. Bottom-Up Health Index Through Multiplication

The framework employs a radical bottom-up construction with an multiplication logic at every aggregation step. The process is executed in three stages:

Leaf Node Assessment: At the lowest level of the tree, an individual measurement channel is transformed into a normalized Health Index (HI). All raw sensor data is collected and stored in an on-premise database. A leaf node does not always represent a raw sensor signal but rather a meaningful diagnostic parameter s, which is often the result of pre-processing:

> **Direct Sensor Values:** The parameter s is a direct, unprocessed signal, such as oil temperature.
>
> **Calculated Values:** Simple conversions, such as converting a tank height sensor reading (mm) into a tank volume (Liters).
>
> **Synthesized Parameters:** Complex metrics derived from multiple inputs, such as the heat exchanger efficiency calculated from temperatures and flow rates.
>
> **State-Dependent Metrics:** Values evaluated only when the system is in a specific state, such as assessing a valve characteristic during quasi-stationary periods.

The subsequent transformation of this parameter s into a normalized Health Index (HI) between 0 (complete failure) and 1 (perfect health) is performed by the expert-calibrated function $f(s)$.

Branch Node Aggregation: The health indices of all channels belonging to a single component or subsystem (a "branch") are aggregated into a single subsystem HI. Instead of averaging, we use the multiplication operator:

$$\boldsymbol{HI_{subsystem} = \Pi\,(HI_1, HI_2, \dots, HI_n)} \qquad \text{Equation 3-1}$$

This approach is deliberately chosen to compound the negative effect when multiple issues arise within the same subsystem. It ensures that the severity of the alert escalates when multiple concurrent faults are present, reflecting a more critical state. A pump unit with two moderately degraded parameters is considered less healthy than a unit with only one, a nuance that a min ( ) operator would miss.

While multiplication is the standard for assessing production readiness, it is important to note that alternative aggregations (e.g., weighted averages for specific sub-goals) are possible and can be configured in coordination with the plant operator.

System-Level Aggregation: Finally, the health indices of all subsystems are aggregated into the single, overall System Health Index (SHI), again through multiplication:

$$\boldsymbol{SHI_{system} = \Pi\, HI_{subsystem}} \qquad \text{Equation 3-2}$$

This consistent use of multiplication acts as a logical AND operator at every level. This approach is crucial for production assurance, ensuring any degradation at any level is immediately and unambiguously reflected in the final score.

4. IMPLEMENTATION STRATEGY

The successful modernization of an operational brownfield system hinges on the pragmatism of its implementation. Deploying a new monitoring framework in a live industrial environment, without interrupting production and on a constrained budget, requires a strategy that prioritizes immediate value, minimizes risk, and builds trust with the existing maintenance crews. Our approach was founded on two core principles: first, maximizing the diagnostic potential of existing infrastructure, and second, deploying the system in self-contained, value-driven modules. This stands in contrast to all-in-one solutions or model-based approaches which can require extensive upfront system modelling before any results are delivered [10].

4.1. Leveraging Existing Infrastructure

Our primary objective was to achieve maximum insight with minimal hardware intervention. This principle of using a small, targeted number of sensors is based on several strategic considerations:

- **Suitability for Brownfield Plants:** It allows for the maximum utilization of signals that are already available.
- **Rapid Deployment:** A minimally invasive approach enables installation and commissioning without production downtime.
- **Reduced Complexity:** Focusing on a few key indicators with clear diagnostic value is more effective than managing a deluge of data points.
- **Ensuring generalization:** The methodology is designed to be applicable across multiple plants and system configurations.

An audit of the plant's existing instrumentation revealed about 50 signals already installed for basic control but unutilized for condition monitoring. These included pressure transmitters, temperature sensors, cooling circuit on/off-signals, and position feedback sensors. While this provided a strong foundation, four new sensor types were added to close key diagnostic gaps:

1. **Ultrasonic flow meters** were installed on each pump leakage drain pipe. This enables a direct comparison of in-production pump performance against datasheet limits, a measurement typically only possible on a test rig [12].

2. **Multiple temperature sensors** were mounted on the main cooling unit to calculate the thermal power being extracted, providing direct insight into the thermal health of the system.

3. **A particle counter** was integrated into the main return line for continuous tracking of oil contamination, a validated method in industrial hydraulics [13].

4. **A high-resolution oil level sensor** was installed inside the reservoir to precisely track the system's total oil volume, making it a highly sensitive tool for detecting small, persistent external leaks.

This philosophy of using a small number of strategically placed sensors is supported by other research where system-level properties have been successfully modelled using common control signals [14]. The additional hardware investment for this upgrade was in the low single-digit percentage range of the original plant investment, a stark contrast to the costs of production stops and emergency maintenance that can accumulate over a year.

4.2. Module-by-Module Deployment

To manage risk and foster adoption, the health tree was rolled out incrementally, module by module. The first module implemented was external leakage monitoring. Using data from the new high-resolution level sensor, it identified a small leak that had previously gone unnoticed, immediately proving the system's value and building trust. Following this, the cooling system health module was activated, using existing temperature sensors and a mass flow calibration from a non-persistent flow meter to track heat exchanger efficiency. Subsequently, modules for pump and valve health were deployed, providing continuous performance data.

A practical method for assessing pump condition involves comparing the measured drain flow with predefined baseline values derived from theoretical nominal flow calculations. The optimal conditions for monitoring the case drain flow are those under which the flow reaches its maximum, specifically:

- Dead head (nearly zero delivered flow rate)
- Constant nominal speed
- Constant nominal pressure

The case drain flow of axial-piston variable displacement pumps is a key indicator for evaluating internal leakage and overall pump efficiency. Monitoring this flow allows for early detection of wear-related degradation, particularly when manufacturer-provided leakage data is unavailable.

The servo valves play an important role within the gap and force control system. Three indicators have thus far been evaluated as health indices for each servo valve within the valve block and cylinders: null bias shift (NBS), signal deviation, and rated flow rate.

1. Null bias shift (NBS): This parameter reflects the tendency of a valve to drift from its neutral position as a result of variations in temperature, supply pressure, or internal leakage occurring in downstream components. In such situations, correction of the electrical current or adjustment of the mechanical null screw is required to re-establish the precise neutral point. Any deviation in the null position introduces errors in closed-loop systems, particularly in positional servomechanisms or pressure control applications, and is especially critical in zero-lapped valves.
2. Signal deviation: In electrohydraulic cylinders controlled by servo valves, control accuracy is determined by the dynamic relationship between the command signal (setpoint) and the feedback signal (measured response). Signal deviation is therefore defined as the difference between these two signals.
3. Rated flow rate: Assessing the actual flow characteristics is essential to compare the rated flow specified in the manufacturer's datasheet with the experimentally measured flow rate. Two degradation trends may be observed. An increase in the rated flow over time indicates spool wear, which enlarges the effective cross-sectional area of the spool ports. Conversely, a decrease in the rated flow signifies increased internal leakage in downstream components.

5. RESULTS FROM SEVEN MONTHS OPERATION

The ultimate measure of any industrial monitoring system is its tangible impact on plant availability, maintenance efficiency, and operational stability. Over a seven-month period of continuous operation, the health tree framework has transitioned from a pilot project to an indispensable tool for the maintenance team. Its success can be measured across four distinct areas: a direct comparison of system response, the technical detection of incipient failures, the cultural transformation of maintenance practices, and the resulting economic benefits.

5.1. *Comparative Baseline and System Response*

A comparison of system behaviour over two consecutive 7-month intervals provides the clearest evidence of the framework's impact. In the period before live monitoring, retrospective analysis of historical data shows that the System Health Index (SHI) dropped to as low as 8% during fault events. This extremely low score reflects the late discovery of issues where degradation was allowed to progress to a catastrophic state before manual detection.

In the subsequent 7 months with the active health tree, the SHI never fell below 70%. This stark difference is not due to a lack of faults, but rather the system's ability to trigger alarms early - typically when health drops from 100% to the 85-90% range. This enables proactive decisions long before a critical state is reached, effectively "flattening the curve" of degradation.

Notably, the number of fault-initiating events was of a similar magnitude in both periods; the crucial difference lies in the system's ability to make degradation visible in real-time.

Crucially, this multiplication logic does not lead to a permanently low system score (e.g., three 80% healthy pumps resulting in ~50% system health), as might be feared in a purely wear-based assessment. This is because our "Health Index" measures production readiness, not just physical wear. A pump with 80% remaining physical life can still be assigned a hight Health Index like 98% if its performance is fully sufficient to ensure production targets. This distinction allows the system to remain sensitive to critical deviations without generating constant, low-level alarms for functional but aging components.

For this comparison, the historical baseline was retrospectively calculated using the identical leaf functions $f(s)$ as the live system.

5.2. *Detected Anomalies and Prevented Failures*

The system's ability to provide early warnings was validated on multiple occasions:
Leakage Prevention:
The early detection of an external leak, identified by the "Leakage Health" module prevented a potential emergency shutdown. More importantly, it averted product quality issues that arise from hydraulic oil contaminating the cooling water or emulsion—a subtle degradation that, without monitoring, is often discovered days later during quality control checks.
Heat Exchanger Performance:
As ambient temperatures rose, combined with maintenance work on the plant's water management system, the "Cooling Health" index showed a progressive decline. This

visualized the decreasing efficiency of the main heat exchanger due to warmer inlet cooling water, allowing the team to proactively adjust production schedules.

Valve Health Verification:

The in-situ determination of valve characteristics via the "Valve Health" module showed a strong correlation with a manual valve measurement performed during a machine shutdown. This confirmed the system can support the definition of maintenance intervals and potentially justify component replacement without requiring external characteristic measurements.

5.3. Transformation of Maintenance Culture

Perhaps the most significant impact of the health tree framework transcends technical metrics. It has transformed the daily workflow and mindset of the maintenance crew.

Team members report a marked reduction in stress associated with unexpected failures. The system typically provides a 4- to 12-hour advance warning of developing issues, shifting the team from a reactive, firefighting mode to a proactive, planning mode. This newfound predictability allows for better coordination with production planning and provides maintenance managers with clear, data-backed justifications for necessary interventions.

One senior technician summarized the change perfectly: "For 20 years, I knew something was wrong from the sound, but I could never explain it to management. Now the health score system shows exactly what I hear, with numbers they understand."

The system has not replaced human expertise; it has amplified it.

5.4. Economic Impact

The economic benefits became apparent through a fundamental shift in operational efficiency:

The primary value is realized through avoided ad-hoc emergency deployments, the ability to conduct planned interventions, and the significant reduction of risks to both product quality and overall plant availability. While concrete monetary figures vary depending on the production context, the swift transition from reactive to proactive maintenance has generated a clear and positive financial impact.

As plant personnel universally acknowledge, the true value lies in the unquantifiable benefits of risk mitigation and enhanced stability for the entire production process.

6. 6. DISCUSSION

The health tree's effectiveness stems from a series of deliberate methodological choices that directly address the operational, cultural, and economic realities of aging factories.

6.1. Why Aggressive Multiplication Works

The framework's consistent use of multiplication for aggregation is a deliberate departure from conventional methods. It avoids the failure-masking flaw of weighted averages while also capturing the compounding risk of multiple concurrent faults—a nuance lost when only considering the single worst value (a min() operator). A focused on system optimization might tolerate averaging, but this fundamentally fails for production assurance.

Production in a rolling mill is often binary—either the product meets strict quality specifications, or it does not. The health tree's multiplication acts as a deterministic logical AND operator at every level, ensuring that any degradation threatening production readiness is immediately and unambiguously reflected in the final score.

While this multiplication deliberately maps production readiness, alternative aggregations (e.g., weighted averages for specific sub-goals) are possible and can be configured on a project-specific basis with the plant operator. However, transparent multiplication remains the standard for ensuring overall production security.

6.2. The Role of Localization: Awareness before Pinpointing

A key aspect of this resource-efficient strategy is the focus on awareness over precise localization. The primary goal is to make developing problems visible to the expert team early. Maintenance crews with years of plant-specific knowledge are highly effective at pinpointing the physical source of a fault once they are alerted to its existence. Providing a general but robust early warning, therefore, delivers the highest value by leveraging this existing human expertise. A more granular, sensor-intensive localization is technically feasible but economically complex and is reserved for future expansion stages.

6.3. Scalability Through Methodology, Not Standardization

The framework is designed to be scalable across different facilities, not through rigid standardization of thresholds, but through the replication of its core methodology. Each new plant implements the same proven approach:

1. **Map the physical plant architecture** to a logical tree structure.
2. **Audit available sensors and identify** critical diagnostic **gaps**.
3. **Implement a data pre-processing layer** to convert raw signals into meaningful diagnostic parameters.
4. **Empower local domain experts** to define operational boundaries independently for each leaf node's diagnostic parameter.
5. **Aggregate health indices** from the bottom up using the deterministic multiplication logic.
6. **Visualize** the results through intuitive, hierarchical dashboards.

This approach allows the specific health functions and thresholds to remain entirely plant-specific, respecting the autonomy and empowering the expertise that exists at each individual site.

6.4. Limitations and Future Development

The current implementation, while successful, also illuminates clear paths for future enhancement. The framework's modularity is one of its greatest strengths. One limitation is that the operational boundaries are static. Future versions could implement dynamic thresholds that adapt to the specifications of the product currently being manufactured. Furthermore, a key future development is the implementation of a prognostic layer at the leaf node level. This would involve extrapolating the observed degradation trend to provide an estimated operational time window before a critical threshold is breached, analogous to a ‘range indicator’ in a vehicle.

Finally, the current focus is explicitly on production health rather than direct component wear. While this was a deliberate choice, the framework is fully compatible with integrating more advanced wear monitoring methods. For instance, methods for tracking pump performance degradation through case drain flow analysis [12] represent a prime candidate for a future “leaf” in the health tree, allowing for better prediction of the remaining useful life of key components.

7. Conclusion

This paper presented a novel health tree framework for the condition monitoring of brownfield industrial hydraulic systems. By combining a hierarchical structure, an aggressive multiplication-based aggregation logic, and an intuitive graphical interface for capturing expert knowledge, the system successfully bridges the gap between decades of hands-on experience and the need for digital oversight. The implementation in a live rolling mill demonstrated that a resource-efficient approach can yield a significant and rapid return on investment. The framework not only prevented unplanned downtime but also fostered a proactive maintenance culture. This work provides a practical and scalable methodology for extending the operational life and reliability of critical aging assets.

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Biographies

Reiner Stammberger received his diploma in hydraulic engineering from TU Dresden in 1989 and joined SMS subsequently. Having engineered countless hydraulic systems for various steel mill applications all over the world, he switched to the fluid service department in 2007. As senior project manager and engineer he is responsible for modernisations and development projects with regard to fluid systems. In this position he can draw from centuries of experience in the steel and hydraulic industry.

Arne Platzbecker received the B.Sc. and M.Sc. degrees in mechanical engineering from RWTH Aachen University, Germany in 2020 and 2022 respectively. In 2022 he joined SMS group in Mönchengladbach for a two-year trainee program with focus towards fluid engineering. In his current position he supports customers to improve their fluid systems in the aftermarket and is responsible for the hydraulic test benches from SMS group around the world..

Joachim Nagelmann has been working at SMS in the IIoT and SmartSensor Solutions division since 2022 and has many years of experience in industrial automation as well as industrial data processing. In his current research project, he is investigating hydraulic systems using modern IIoT technologies to advance data-driven industrial optimizations.

Maximilian Schmidt received the Diplom-Ingenieur degree in mechanical engineering from TU Dresden, Germany, in 2017, and worked at thyssenkrupp Carbon Components GmbH until 2022, developing resin transfer moulding production systems and digitalization solutions for automotive manufacturing. Since 2022, he has been a Research Associate at the Chair of Fluid-Mechatronic Systems (Fluidtronics) at TU Dresden, where his research focuses on developing physics-based condition monitoring frameworks for industrial hydraulic systems, bridging domain expertise with modern information technology for predictive maintenance applications.

Ahmad Al-Issa received the B.Sc. and M.Sc. degrees in mechanical engineering from AL-Mustansiriya University, Baghdad, Iraq in 2009 and 2012, respectively. This was followed by approximately 2 years as a university lecturer and then a 6-year industrial phase as a hydraulic engineer at General Company for Grain Processing, Ministry of Trade, Baghdad, Iraq. Currently, he is a research assistant and pursuing his PhD degree at Chair of Fluid-Mechatronic Systems, TU Dresden, Germany. His research focuses on thermal analysis and energy condition monitoring of complex industrial hydraulic systems.

Tobias Schulze is working as a research associate and pursuing his Ph.D. at the Chair of Fluid-Mechatronic Systems (Fluidtronics) at TU Dresden, Germany. He serves as the team leader for the Fluid-Mechatronic Systems Group, with his research focusing on stationary hydraulic systems, specifically hydraulic deep drawing presses and electrohydraulic compact drives.

an estimated operational time window before a critical threshold is breached, analogous to a ‘range indicator’ in a vehicle.

Finally, the current focus is explicitly on production health rather than direct component wear. While this was a deliberate choice, the framework is fully compatible with integrating more advanced wear monitoring methods. For instance, methods for tracking pump