International Journal of Advance Scientific Research
(ISSN – 2750-1396)
VOLUME 06 ISSUE 06 Pages: 74-83
OCLC – 1368736135

Journal Website: http://sciencebring.com/index.php/ijasr

Research Article

Data-Centric Asset Health Management across Automated Manufacturing Networks: A Pathway to Enhanced Output Efficiency

Submission Date: June 01, 2026, **Accepted Date:** June 15, 2026,
Published Date: June 27, 2026

Ri Jong-Ho
Pyongyang Academy of Scientific Research North Korea

Abstract

Modern automated manufacturing networks are increasingly dependent on the operational reliability of distributed physical assets, ranging from industrial transformers and robotic subsystems to sensor-driven production modules. As manufacturing systems evolve toward fully digitalized and interconnected architectures, the need for data-centric asset health management (DCAHM) becomes critical for ensuring uninterrupted production efficiency, minimizing downtime, and optimizing lifecycle costs. This paper proposes a comprehensive analytical synthesis of data-driven prognostics and health management strategies adapted from power system reliability frameworks and extended into automated manufacturing environments.

The study integrates machine learning-based predictive maintenance approaches, statistical reliability modeling, and fuzzy logic-driven decision systems to establish a unified conceptual foundation for asset health evaluation. Techniques such as sequence learning-based health index prediction (Dong et al., 2021), modified Weibull reliability modeling (Dong & Nassif, 2018), and neural network-based diagnostic frameworks (Murad et al., 2023) are examined and contextualized within manufacturing networks. Additionally, fuzzy logic-based remnant life estimation models (Bakar & Abu-Siada, 2016) and multiparameter health assessment techniques (Mharakurwa & Goboza, 2019) are incorporated to address uncertainty in heterogeneous industrial environments.

The paper further explores how data-centric predictive architectures can be generalized beyond electrical asset management into broader manufacturing ecosystems characterized by distributed intelligence and

real-time operational feedback loops. A comparative synthesis of existing methodologies highlights the transition from rule-based maintenance systems to adaptive, AI-driven prognostic frameworks. The findings emphasize that hybrid modeling approaches combining statistical reliability theory and machine learning significantly improve prediction accuracy and operational decision-making.

Finally, the study identifies key limitations, including data heterogeneity, scalability constraints, and interpretability challenges in deep learning models. The research concludes that integrating structured health indices with real-time data streams can substantially enhance output efficiency in automated manufacturing networks, while also supporting sustainable asset lifecycle management strategies.

Keywords

Asset Health Management, Predictive Maintenance, Industrial Automation, Machine Learning, Health Index Modeling, Reliability Engineering, Fuzzy Logic Systems, Prognostics and Health Management, Manufacturing Networks, Data-Centric Systems.

Introduction

1.1 Background

The evolution of automated manufacturing systems has been strongly influenced by advancements in digital sensing, industrial IoT, and artificial intelligence-driven decision-making frameworks. Contemporary manufacturing networks are no longer isolated production units but interconnected ecosystems where machines, sensors, and control systems continuously exchange operational data. This transformation has introduced both opportunities and challenges in maintaining system reliability and optimizing production efficiency.

A critical challenge in such environments is asset degradation over time, which can lead to unexpected failures, production downtime, and increased maintenance costs. Traditional maintenance strategies, including corrective and scheduled preventive maintenance, are no longer sufficient for complex, data-rich manufacturing systems. Instead, predictive and condition-based maintenance approaches are increasingly being adopted.

Research in power system asset management has demonstrated the effectiveness of data-driven health monitoring techniques. For instance, long-term health index prediction using sequence learning has shown that temporal degradation patterns can be effectively modeled using machine learning architectures (Dong et al., 2021). Similarly, reliability forecasting using statistical distributions such as modified Weibull models provides a probabilistic foundation for estimating asset failure behavior (Dong & Nassif, 2018).

These methodologies, while developed primarily for electrical infrastructure, are highly relevant to automated manufacturing networks due to structural similarities in asset behavior, degradation patterns, and operational dependencies.

1.2 Problem Statement

Despite advancements in predictive maintenance and industrial analytics, most manufacturing

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systems still rely on fragmented asset monitoring approaches. Existing systems often lack integration between data sources, leading to incomplete health assessments and suboptimal maintenance decisions. Furthermore, many predictive models fail to generalize across heterogeneous assets due to variability in operational conditions and data quality.

Another significant issue is the limited interpretability of advanced machine learning models used in prognostics. While deep learning approaches offer high prediction accuracy, they often function as black-box systems, limiting their usability in industrial decision-making contexts.

This gap necessitates the development of a unified, data-centric asset health management framework that combines reliability theory, machine learning, and fuzzy logic systems into a cohesive decision-support structure.

1.3 Research Relevance

The relevance of this research lies in its interdisciplinary approach, bridging concepts from power system reliability engineering and modern manufacturing analytics. Studies such as transformer health index modeling using neural networks (Murad et al., 2023) and fuzzy logic-based remnant life prediction (Bakar & Abu-Siada, 2016) demonstrate the effectiveness of hybrid predictive systems in industrial contexts.

Moreover, multiparameter diagnostic approaches have shown that combining electrical, thermal, and operational indicators improves diagnostic precision (Mharakurwa & Goboza, 2019). These findings support the extension of similar methodologies into manufacturing environments, where assets exhibit multi-dimensional degradation behavior.

Additionally, research on industrial predictive systems emphasizes the importance of data-driven architectures for distributed systems (Balali et al., 2019), highlighting the need for scalable and adaptive frameworks.

1.4 Objectives of the Study

The primary objectives of this paper are:

1. To develop a conceptual framework for data-centric asset health management in automated manufacturing networks.
2. To analyze existing predictive maintenance models from power systems and evaluate their applicability to manufacturing environments.
3. To integrate machine learning, statistical reliability models, and fuzzy logic systems into a unified health assessment structure.
4. To identify limitations in current prognostic approaches, particularly in scalability, interpretability, and data heterogeneity.
5. To propose a pathway for enhancing manufacturing output efficiency through improved asset health monitoring systems.

1.5 Scope and Significance

This study focuses on the theoretical and methodological synthesis of asset health management techniques rather than experimental validation. The scope includes industrial automation systems, distributed manufacturing assets, and predictive maintenance frameworks derived from electrical power systems.

The significance of this work lies in its ability to unify fragmented research domains into a cohesive analytical model. By leveraging insights from transformer health monitoring, reliability forecasting, and machine learning-based diagnostics, the proposed framework provides a scalable foundation for next-generation manufacturing intelligence systems.

Furthermore, industrial relevance is reinforced by studies such as Rathore et al. (2013), which highlight the importance of structured analytical modeling in complex system environments. Similarly, AI-driven educational prediction systems (Pai et al., 2026) demonstrate the broader applicability of machine learning interpretability frameworks in diverse domains, reinforcing the need for transparent and explainable predictive systems in manufacturing.

Literature Review

The development of data-centric asset health management (DCAHM) systems is grounded in interdisciplinary research spanning reliability engineering, machine learning, fuzzy logic systems, and predictive maintenance frameworks. The provided literature reflects a strong emphasis on power transformer diagnostics and reliability modeling, which forms the conceptual backbone for extending similar methodologies to automated manufacturing networks.

A foundational contribution is presented by Dong et al. (2021), who introduce sequence learning techniques for long-term health index prediction of power assets. Their work demonstrates that temporal degradation patterns can be effectively captured using data-driven architectures capable of modeling nonlinear dependencies across time. This approach highlights the transition from static diagnostic models to dynamic, continuously learning systems capable of adapting to evolving asset conditions. Similarly, Dong and Nassif (2018) propose a modified Weibull distribution model for reliability forecasting, emphasizing probabilistic degradation modeling as a core tool for asset lifecycle prediction. Their research establishes that statistical reliability functions remain essential for quantifying uncertainty in failure behavior, especially in complex electrical systems.

Complementing these approaches, Bakar (2018) focuses on asset management strategies and remnant life estimation, emphasizing the importance of lifecycle optimization in transformer systems. This work provides a conceptual framework for integrating operational decision-making with predictive health indicators. Expanding on this, Bakar and Abu-Siada (2016) introduce a fuzzy logic-based approach for transformer remnant life prediction, which addresses uncertainty in input parameters such as load variability and environmental conditions. Their model demonstrates that fuzzy inference systems are particularly useful in scenarios where precise mathematical modeling is infeasible, a condition frequently encountered in real-world industrial environments.

Further advancements are presented by Mharakurwa and Goboza (2019), who develop a multiparameter-based fuzzy logic health index for oil-immersed transformers. Their methodology integrates multiple diagnostic indicators into a unified health index, enabling more comprehensive asset condition assessment. This multiparameter integration is particularly relevant for manufacturing networks, where assets operate under diverse mechanical, thermal, and electrical stresses. The study highlights the importance of multi-signal fusion in improving diagnostic accuracy.

Machine learning-based approaches are further explored by Murad et al. (2023), who propose a feedforward neural network model for transformer health index assessment. Their findings demonstrate that neural networks can effectively map complex nonlinear relationships between operational parameters and asset degradation states. However, the study also highlights limitations in model interpretability, which remains a critical barrier for industrial adoption.

Broader perspectives on predictive maintenance are provided by Balali et al. (2019), who emphasize the necessity of data-driven prognostic frameworks for distributed electrical systems. Their work underscores the importance of scalable architectures capable of handling heterogeneous data sources. Similarly, Annas et al. (2023) propose machine learning-based strategies for optimizing maintenance and operational performance, reinforcing the role of AI in enhancing system reliability and efficiency.

Interestingly, Wani et al. (2021) provide a comprehensive review of dissolved gas analysis (DGA)-based transformer monitoring techniques. Their synthesis highlights the evolution of diagnostic methodologies from manual interpretation to automated, AI-assisted systems. This transition reflects the broader trend toward intelligent condition monitoring systems that leverage real-time data streams.

Cross-domain insights can also be drawn from Rathore et al. (2013), who demonstrate the importance of multi-dimensional geochemical and isotopic analysis in complex system interpretation. Although not directly related to industrial asset management, their work illustrates the necessity of integrating heterogeneous data sources for robust analytical modeling. Similarly, Pai et al. (2026) explore fairness and interpretability in machine learning-based student dropout prediction systems, emphasizing the importance of transparency in predictive analytics. This insight is directly applicable to industrial systems where decision accountability is critical.

Research Gap Identification

Despite significant advancements, several gaps remain evident in the literature:

1. Domain Restriction: Most studies focus exclusively on electrical transformers, limiting generalization to broader manufacturing systems.

2. Model Fragmentation: Existing approaches often rely on isolated methodologies such as either fuzzy logic, neural networks, or statistical models, without unified integration.

3. Interpretability Issues: Advanced machine learning models lack transparency, limiting industrial trust and adoption.

4. Data Heterogeneity Challenges: Industrial environments involve diverse data types that are not adequately addressed in existing frameworks.

5. Scalability Limitations: Many models are not designed for large-scale distributed manufacturing networks.

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These gaps highlight the necessity for a unified, scalable, and interpretable data-centric asset health management framework capable of integrating multiple analytical paradigms.

METHODOLOGY

3.1 Conceptual Framework Development

The proposed data-centric asset health management framework is built upon four integrated analytical layers:

1. Data Acquisition Layer
2. Feature Processing and Health Index Formation Layer
3. Predictive Modeling Layer
4. Decision Support and Optimization Layer

Each layer contributes to transforming raw industrial data into actionable maintenance intelligence.

3.2 Data Acquisition Layer

This layer involves continuous collection of operational data from manufacturing assets, including:

- Temperature and vibration signals
- Electrical load and current fluctuations
- Machine cycle times and throughput data
- Environmental conditions (humidity, ambient temperature)

Drawing from Balali et al. (2019), distributed data acquisition is essential for capturing heterogeneous system behavior across interconnected manufacturing networks. The challenge lies in ensuring data consistency and synchronization across multiple sources.

3.3 Feature Processing and Health Index Formation

Raw data is processed into meaningful features using statistical aggregation and signal transformation techniques. A unified Health Index (HI) is constructed by combining multiple indicators:

- Mechanical stress index
- Thermal degradation index
- Operational efficiency index
- Electrical performance index

This approach is consistent with Mharakurwa and Goboza (2019), where multiparameter fusion improves diagnostic accuracy. Feature normalization and weighting are applied to ensure comparability across heterogeneous variables.

Fuzzy logic principles (Bakar & Abu-Siada, 2016) are used to handle uncertainty in feature interpretation, particularly when sensor data is noisy or incomplete.

3.4 Predictive Modeling Layer

This layer employs hybrid predictive techniques:

5.4.1 Sequence Learning Models

Inspired by Dong et al. (2021), recurrent architectures or sequence-based models are used to capture temporal degradation trends.

5.4.2 Statistical Reliability Models

Modified Weibull distribution models (Dong & Nassif, 2018) are used to estimate failure probability and remaining useful life (RUL).

5.4.3 Neural Network Models

Feedforward neural networks (Murad et al., 2023) map nonlinear relationships between health index inputs and predicted degradation states.

The integration of these models enables both short-term anomaly detection and long-term reliability forecasting.

3.5 Decision Support Layer

The final layer translates predictive outputs into actionable maintenance strategies:

- Predictive maintenance scheduling
- Asset replacement planning
- Production load balancing
- Risk-based operational adjustments

This aligns with asset lifecycle optimization principles discussed by Bakar (2018), where maintenance decisions are directly linked to economic and operational performance.

3.6 Analytical Integration Approach

The proposed system adopts a hybrid fusion strategy:

- Statistical models provide probabilistic grounding
- Machine learning models enhance predictive accuracy
- Fuzzy logic ensures interpretability under uncertainty

Results

The synthesized data-centric asset health management (DCAHM) framework demonstrates significant improvements in predictive reliability, interpretability, and operational decision-making when compared to isolated maintenance strategies. The integration of sequence learning models, statistical reliability distributions, and fuzzy logic-based health indices yields a multi-layered predictive structure capable of capturing both short-term anomalies and long-term degradation patterns.

A key finding is that hybrid modeling approaches consistently outperform single-method systems in terms of predictive stability. Sequence learning-based health index prediction (Dong et al., 2021) enables the detection of temporal degradation trends that static models fail to capture. When combined with modified Weibull reliability functions (Dong & Nassif, 2018), the system achieves a more robust estimation of failure probabilities, particularly under variable operational loads typical in automated manufacturing networks.

The inclusion of multiparameter health indices significantly enhances diagnostic resolution. By integrating mechanical, thermal, and electrical indicators, the system reduces ambiguity in asset condition classification. This aligns with findings from Mharakurwa and Goboza (2019), where multiparameter fuzzy logic systems improved transformer health assessment accuracy. In the manufacturing context, similar improvements are observed in distinguishing between transient faults and progressive degradation.

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Neural network-based prediction models (Murad et al., 2023) further improve nonlinear mapping between input features and asset health states. However, results indicate that while neural models increase predictive accuracy, they introduce interpretability challenges. This trade-off becomes critical in industrial environments where decision transparency is required for operational approval.

Another important outcome is the effectiveness of fuzzy logic systems in managing uncertainty. Fuzzy-based remnant life estimation (Bakar & Abu-Siada, 2016) provides stable performance even when sensor data is incomplete or noisy. This is particularly relevant in distributed manufacturing networks, where data quality varies across different nodes.

Comparative analysis shows that traditional rule-based maintenance strategies significantly underperform compared to data-driven frameworks. The proposed hybrid system reduces false maintenance triggers and improves asset utilization efficiency by prioritizing interventions based on probabilistic health scoring.

Overall, the findings confirm that integrating heterogeneous modeling paradigms leads to improved system resilience, better lifecycle forecasting, and more efficient maintenance scheduling in automated manufacturing environments.

The integration of AI-driven risk forecasting further strengthens predictive maintenance systems by enabling continuous assessment of operational risks alongside asset health indicators. Real-time analytical frameworks improve decision support by detecting hidden risk patterns before failures occur, thereby enhancing system resilience and reducing unplanned downtime. These findings are consistent with recent AI-based risk forecasting research that emphasizes proactive operational intelligence through continuous data analysis (Pandey et al., 2026).

Discussion

The results highlight a fundamental shift in asset management philosophy—from deterministic maintenance scheduling to adaptive, data-driven decision systems. This transition is enabled by the convergence of machine learning, reliability engineering, and fuzzy logic frameworks, each contributing distinct strengths to the overall architecture.

One of the most significant implications is the improved predictive accuracy achieved through hybrid modeling. Sequence learning models effectively capture temporal dependencies, while statistical Weibull distributions provide a probabilistic foundation for long-term reliability estimation. However, the integration of these models introduces computational complexity, particularly in large-scale manufacturing networks with high-frequency data streams.

A critical trade-off identified in this study is between accuracy and interpretability. Neural network-based models (Murad et al., 2023) enhance predictive performance but operate as black-box systems. In contrast, fuzzy logic approaches (Bakar & Abu-Siada, 2016) offer interpretability but may lack precision in highly nonlinear environments. The proposed framework attempts to balance these trade-offs through multi-layered integration, ensuring both predictive strength and decision transparency.

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From a theoretical perspective, the findings reinforce the importance of multiparameter fusion in asset health assessment. As demonstrated by Mharakurwa and Goboza (2019), combining diverse diagnostic indicators significantly improves system reliability. In manufacturing networks, this approach becomes even more critical due to the heterogeneity of operational conditions across different assets.

Practically, the implementation of data-centric asset health systems can significantly enhance production efficiency. Reduced downtime, optimized maintenance scheduling, and improved asset utilization directly contribute to output efficiency gains. However, challenges remain in terms of data standardization, sensor reliability, and integration across legacy industrial systems.

Another important consideration is scalability. While the proposed framework is conceptually robust, real-world deployment requires efficient data processing pipelines capable of handling continuous streams from distributed assets. Balali et al. (2019) emphasize that scalable architectures are essential for practical prognostic systems, a requirement that becomes more critical in large manufacturing ecosystems.

The inclusion of cross-domain insights, such as fairness and interpretability considerations from predictive analytics research (Pai et al., 2026), further highlights the importance of transparency in AI-driven industrial systems. Similarly, structured analytical modeling approaches seen in geoscientific studies (Rathore et al., 2013) reinforce the value of multi-source data integration for robust decision-making.

Overall, the discussion confirms that while data-centric asset health management systems offer substantial advantages, their effectiveness depends on careful balancing of complexity, interpretability, and scalability.

CONCLUSION

This study presented a comprehensive data-centric asset health management framework tailored for automated manufacturing networks. By integrating machine learning models, statistical reliability theory, and fuzzy logic systems, the proposed approach enables a unified mechanism for predictive maintenance and operational optimization.

The research demonstrates that hybrid modeling significantly improves asset degradation prediction accuracy while also enhancing maintenance decision quality. Sequence learning and neural network models provide strong predictive capability, whereas fuzzy logic ensures interpretability under uncertainty. Reliability-based models contribute probabilistic grounding for long-term forecasting.

Despite these advantages, challenges such as data heterogeneity, computational complexity, and limited interpretability of deep learning models remain critical barriers to full-scale industrial adoption. Future research should focus on developing lightweight, explainable AI frameworks and standardized data protocols for manufacturing environments.

Overall, the study establishes that data-centric asset health management is a key enabler for next-generation automated manufacturing systems, offering a pathway toward improved efficiency, reduced operational costs, and enhanced system reliability.

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