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A Comparative Review of Model Driven Control and Data Driven Machine Learning for Manufacturing, Monitoring, Inspection and Optimization: Nigerian Adaptability

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ABSTRACT

Review Article

Practical automation in autonomous condition assessment of physical assets is one of the obvious central goals of the fourth (4th) Industrial revolution majorly known with Cyber - Physical Systems; IoT and Big Data; AI & Machine Learning; Cloud, Edge Computing and Connectivity. Unfortunately, research on robotic inspection of civil infrastructure and intelligent fault diagnosis for machinery has evolved largely concurrently and, in some cases, almost simultaneously.

This review provides a comparative analysis of these two domains as examined independently in already existing literatures. The six key study areas covered in this review are: Unmanned Ariel Vehicle (UAV), Unmanned Ground Vehicle (UGV), Inspection, Ellipsoidal obstacle avoidance, Noise-robust fault diagnosis, Vibration image-based classification, and Transfer learning for tool wear detection. Comparative reviews were made using Sensing modalities; Machine learning strategies; Real-time constraints; and Validation practices across both fields. Results substantially concur with the results of previous researches that Fault diagnosis research leads in handling data scarcity, noise robustness, and domain adaptation, while Inspection research leads in multi-modal sensor fusion and field deployment. However, it further shows that both domains experience shared challenges in Benchmarking, Edge deployment, Explainability, and Certification, while three convergent areas were identified in: Transfer learning to reduce data needs in inspection; Edge optimization techniques from inspection to inform diagnosis deployment, and Causal explainability to build engineer trust. Interestingly, the review concludes with a research agenda focused on Cross-domain benchmarks, Tiny Machine Learning deployment, and Certification-ready architectures. It further suggests that unifying these streams will accelerate the adoption of autonomous asset management across infrastructure and manufacturing, while proffering conditions for the suitability and adaptability of the results of the review to the Nigerian engineering space.

Keywords: Comparative, Model - Driven, Data - Driven, Machine Learning, Inspection, Manufacturing, Monitoring, Optimization, Transfer Learning, Adaptability.

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Introduction

There is no doubt that the fourth and emerging fifth industrial revolutions have accelerated the integration of sensing, computation, and automation into manufacturing systems (Halder & Afsari, 2023). At the core of this transformation are obviously two dominant paradigms for system control and decision-making: model-driven control and data-driven machine learning. Shi, X., & Yang, Y., (2026) summit that

Model-driven approaches rely on first-principles physics, differential equations, and analytical models to describe process dynamics, enabling deterministic control and optimization of operations such as machining, grinding, and additive manufacturing. In contrast, Li, X., et al., (2020) is of the opinion that:

“Data-driven machine learning methods leverage historical and real-time data to identify patterns, predict faults, and optimize processes with minimal reliance on explicit physical models.”

Interestingly, both paradigms address critical manufacturing functions to wit: monitoring, inspection, and optimization, but fundamentally differ in their assumptions, data requirements, computational demands, and adaptability to process variability. Furthermore, Chen, Y. et al. (2020) observed that Model-driven control provides interpretability and robustness in well-characterized systems, though it often struggles with nonlinearities, non- modeled dynamics, and the high cost of model development for complex processes. Conversely, Lei et al. (2020) opined that Data-driven machine learning offers flexibility and scalability in handling high-dimensional, nonlinear data from sensors such as vibration, thermal imaging, and vision systems. However, it requires substantial labeled data, faces challenges in generalizability, and often operates as a “black box,” limiting trust in safety-critical applications.

Recent advances and innovations in edge computing, transfer learning, and hybrid modeling have begun to blur the boundary between these paradigms thus offering more flexible Hybrid approaches that combine a mix of physics-informed constraints with data-driven inference. These emerging technological breakthroughs are increasingly applied to predictive maintenance, tool wear diagnosis, and real-time process optimization. Despite this convergence, a systematic comparison of the strengths, limitations, and applicability of model-driven and data-driven methods across the manufacturing lifecycle remains fragmented in the existing literature. Existing reviews tend to focus on a single function such as fault diagnosis or process optimization or on a specific technology, without addressing the broader trade-offs relevant to practitioners and researchers deploying solutions in diverse industrial contexts.

Overview

The studies carried out by Halder & Afsari (2023) on Laser additive manufacturing for alloy repair in high value components and those of Zhao et al. (2019) on the first systematic review showing deep learning beats hand-crafted features for machinery health monitoring on raw signals remain fundamental and informative as a baseline in this research interest. In order to bridge the technological gap created from the rapid innovations like the ones recorded in the areas of Unmanned Ariel Vehicles (UAV)which was an advancement over the Unmanned Ground Vehicles (UGV), ISO 21393: (2020) released the first international UAV operational standard ever, which among others highlights regulatory gaps. However, the work of Lei et al. (2020) in Reliability Engineering for a comprehensive review contrasting data-driven from model-based fault diagnosis methods remains sacrosanct.

Furthermore, the contributions of Wang et al. (2021) in upholding automation in construction space as their findings from a review of UAV bridge inspection shows automation level <30% in actual practice; just as Li et al. (2020) Sensors Survey of multi-sensor fusion strategies; justified vision-LiDAR-thermal fusion. Interestingly, while Rosenfelder, M., et al. (2025) results show that Real-time performance on a wheeled mobile robot is validated in hardware as well, hence, Ellipsoidal modeling reduces conservatism and enables real-time local avoidance;

Hung, N., et al. (2023) results confirm that NMPC and geometric controllers showed best trade-off between accuracy and robustness meaning that

'No single method dominates; choice depends on vehicle dynamics and constraints'. Assessing computational cost and complexity, Rubí, B., Pérez, R., & Morcego, B. (2020) confirmed NMPC handled constraints best but had higher computational cost. hence submitted that 'For aggressive maneuvers, NMPC is preferred if real-time feasible' while Gao, Y., (2024) advocates for real time when asserting that 'Dual formulation reduces computational complexity for ellipsoidal avoidance. Ericson, C. (2020) promotes Standard reference for implementing collision checks in robotics. Ames, A. D., (2019) stood out as it guaranteed set invariance for nonlinear systems in simulation and hardware.

Despite shared goals of reducing downtime and improving safety, both fields of study have evolved separately. Shi & Yang (2026) engaged the Empirical Mode Decomposition (EMD) to preprocess and denoise vibration signal while Adaptive Asymmetric Difference - Phase Imaging (AADPCI) to convert the processed signal into vibration images which are fed into a classifier for fault diagnosis. Chen et al. (2020) paid more attention to mechanism needed to focus on fault-related features, while Han et al. (2021) studied on Feature fusion network for compound fault diagnosis. Liu et al. (2020) critical review of transfer learning for mechanical fault diagnosis was outstanding as the findings support results from Chen et al. (2021) that considered GNN for sensor network -based fault diagnosis while Peng et al. (2022) focused on Benchmarking DL models on standard datasets to achieve standardization.

Moreover, Kasiviswanathan & Gnanasekaran (2026) studied the transfer learning for tool wear; Chen et al. (2020) chose to focus on wear -related features; while Liu et al. (2020) reviewed the transfer learning in mechanical systems.
Peng et al. (2022) prefers to set a standard by considering Benchmarking DL models for tool wear.

Chen et al. (2021) examined GNN for tool wear prediction on multi sensor networks while Han et al. (2021) Feature fusion for multi - sensor tool wear monitoring remain a case study till date.

Fault diagnosis relies on vibration signals captured from rotating machinery under varying loads and noise conditions. Recent work emphasizes noise suppression and multiscale feature extraction to maintain accuracy at low signal-to-noise ratios. Transfer learning has become critical to adapt models to new machines with limited labeled data.

The works of Charde et al. (2026) who studied the outcome of adding machine learning techniques to Particle Swarm Optimization an optimization algorithm for grinding forces.

Yang et al. (2020) focused on transfer learning for cross material process optimization while Wu et al. (2020) delt with reinforcement learning for adaptive machining control. Li et al. (2021) expanded the scope by looking at digital twin for grinding process optimization as Liu et al. (2020) did great work in Deep Learning surrogate for manufacturing process optimization while Zhang et al. (2019) studied NN-based real- time optimization of machining parameters

Methodology

This study uses a well-structured comparative review to unify robotic inspection and predictive maintenance for Nigerian infrastructure and machinery.

Literatures mostly from 2020–2026 were engaged to scale down the number and to retain very close identity to the topic. From the initial pool of three hundred (300) related papers studied, only thirty (30) were later painstakingly selected based on empirical methods and clear performance metrics from the initial pool of well over three hundred (300) literatures.

Studies were further grouped into two: Group A: Model-driven methods (e.g., MPC, physics-based control) and Group B: Data-driven methods (e.g., EMD-AADPCI, transfer learning, ML+PSO). A comparative matrix assessed objectives, sensors, algorithms, accuracy, cost, and deployment constraints. Each method was: later scored against Nigerian constraints—power instability, low bandwidth, cost, and skill gaps—using a weighted rubric. Methods were classified as directly viable, adaptable, or not feasible. Findings were synthesized to map convergence points and gaps, leading to a low-cost, low-bandwidth framework for pilot deployment in Nigerian settings.

Justification

The need to separate model-based control and optimization from those of data-driven machine learning (ML) for manufacturing monitoring, inspection and optimization. The model-based control for manufacturing monitoring, inspection and optimization was reviewed in the studies carried by the duo of: Halder & Afsari (2023) "Laser Additive Manufacturing" who focused on physics-based models for heat transfer, fluid flow, and microstructure in laser AM. The goal is to optimize process parameters to control defects, residual stress, and microstructure using analytical and FEM models; while Rosenfelder et al. (2025) "MPC for obstacle avoidance in mobile robots and vehicles" used Model Predictive Control (MPC) to generate feasible, optimal trajectories for mobile robots and vehicles to avoid ellipsoidal obstacles. It relies on a system dynamics model and constraints. A review of both papers showed a remarkable common ground as:

1. Both use model-based optimization and control of physical systems.
2. Both treat the system as having known or approximated physics.
3. Optimization is performed over a model to satisfy constraints and objectives.
4. No large-scale data-driven learning is required.
5. The emphasis is on interpretability, constraint handling, and safety-critical control.

Contrarily, the data-driven machine learning (ML) approaches for manufacturing process monitoring and optimization were independently examined by the trio of: Shi & Yang (2026) "EMD-AADPCI vibration images for fault diagnosis" who studied the conversion of vibration signals into images and the usage of deep CNNs for fault diagnosis as Feature extraction is learned from data.

Kasiviswana than & Gnanasekaran (2026) "Transfer learning for tool wear" uses transfer learning and domain adaptation to predict tool wear across machines/materials with limited labeled data.

Charde et al. (2026); “ML + PSO for grinding force optimization" builds machine learning surrogate models of grinding forces and uses Particle Swarm Optimization to find optimal parameters.

A review of the three papers showed the following common features:

1. They are all data- driven machine learning (ML) approaches though the magnitude of data engagement varies.
2. They rely on sensor data, statistical/ML models, and minimal physics assumptions
3. The system is too complex or nonlinear to model analytically.
4. The common approach adopted is to learn patterns from data.
5. The major goal remains prediction, diagnosis, or optimization so long as data availability is assured.
6. A first-principles' model is not easily tractable in any of the three studies.

Justification for Comparative Review

Engineering activities are becoming more and more complex by the day. In such a situation where there is a complex manufacturing and robotic systems to handle, there is every need to objectively and unmistakenly identify the right approach to engage for optimal results between model - based optimization or data - driven machine learning (ML), and/or when both may need to complement each other.

Comparative review of the two dominant approaches in the 21st century manufacturing and robotics research: (Model-driven and Data-driven paradigms) in engineering systems using four variables reveals as follows:

Model-Driven

Basis: Physics equations, system dynamics, analytical models.
Strengths: Interpretability, constraint satisfaction, works with little data, safety guarantees.
Weaknesses: Requires accurate models, struggles with unknown dynamics.
Examples: AM melt pool control, MPC for vehicle/robot motion

Data-Driven

Basis: Sensor data, statistical learning, and neural networks.
Strengths: Handles nonlinearity, high-dimensional data, no model needed, adapts to complex processes.
Weaknesses: Needs large data, poor interpretability, can violate physical constraints.
Examples: Tool wear prediction, fault diagnosis, grinding force and optimization.

Relevance of the Comparative Review

This is to further enhance knowledge - based information sensitization to guide wise application and engagement. The three variables used in this review are:

1. **Methodological contrast:** It underscores the variations existing between accuracy, precision, data requirements, computational expense, and ease of explainability.
2. **Application mapping:** Shows when each approach is more appropriate than the other, or when both can complement the other; Model-based appears to work better if physics is known, while data-driven is preferred when it is not available.
3. **Research trend:** This comparison naturally leads to the discussion on the possibility of hybrid of approaches or better still the combination of both approaches 'approach-mix' physics-informed machines Learning L, which is the active research gap in 2025-2026.

Comparative Review Analysis

The selected studies were categorized into two groups based on their methodological approach to enable a structured comparison.

Group A: Model-Based Methods

Studies in this group rely on physics - based models, system dynamics, and optimization over known constraints. Representative studies are those of Halder & Afsari (2023) on laser additive manufacturing process control and Rosenfelder et al. (2025) on model predictive control for obstacle avoidance. The approaches use analytical or numerical models to predict system behavior and compute optimal control actions. Key characteristics extracted include: reliance on governing equations, explicit handling of physical constraints, low requirement for labeled training data, and high interpretability. Performance metrics focused on trajectory accuracy, constraint satisfaction, and computational time for real-time control. The primary limitation observed is the dependence on accurate models and sensors for state estimation.

Group B: Data- Driven Methods

Studies in this group employ machine learning, deep learning, and signal processing to extract patterns directly from sensor data. Representative studies include Shi & Yang (2026) on EMD-AADPCI vibration imaging for fault diagnosis, Kasiviswanathan & Gnanasekaran (2026) on transfer learning for tool wear, and Charde et al. (2026) on ML surrogate models combined with PSO for grinding optimization. Data extracted covered sensor types, signal preprocessing methods, learning algorithms, dataset size, classification or regression accuracy, and inference time. Common strengths are the ability to model complex, non-linear relationships without explicit physics models and adaptability to new machines through transfer learning. Limitations include dependence on large, high-quality datasets, reduced interpretability, and sensitivity to domain shift.

Comparison Framework

A comparative matrix was constructed across six dimensions:

1. Data requirements,
2. Computational cost and latency,
3. Interpretability,
4. Robustness to noise and environmental variation,
5. Adaptability to new equipment or sites, and
6. Deployment feasibility on edge devices.

Deduction

This matrix revealed that Group A methods excel in constraint handling and low-data scenarios, while Group B methods outperform in handling high-dimensional, noisy data and complex fault patterns. The comparison provides the basis for evaluating which approach or hybrid combination is most suitable for resource-constrained environments.

Nigerian Adaptability Assessment

Methods from Group A and Group B were evaluated against Nigeria-specific constraints using a weighted percentage scoring. The criteria and weights were: technical feasibility 30%, capital and operational cost 25%, maintenance burden and spare parts availability 20%, data and connectivity requirements 15%, and local skill requirement 10%.

Findings/Results

Model-driven methods (Group A) score high only interpretability and low data needs, making them suitable where physics models exist and computing resources are limited. However, they require accurate system models and sensors for state estimation, which increases the deployment cost. MPC for obstacle avoidance is feasible for indoor and low-speed UGVs but struggles with GPS-denied outdoor environments common in Nigerian sites.

Data-driven methods (Group B) perform well on complex, non-linear problems like tool wear and fault diagnosis. Transfer learning and lightweight CNNs reduce data and training costs, making them adaptable. The main barrier is intermittent power and poor internet, which limits cloud-based training and inference. Edge deployment on low-cost GPUs or TPUs is required.

Overall Assessment

Vibration-image based diagnosis using EMD-AADPCI and transfer learning models on edge devices ranked highest for adaptability. Pure physics-based MPC and high-resolution laser AM control were rated low due to cost and infrastructure demands.

Synthesis and Framework Development

The review identified two convergence points:

1. Data fusion loop: Images and vibration data from robotic inspection can serve as real-time inputs to predictive maintenance models, reducing manual inspection cycles.
2. Hybrid approach: Embedding simplified physics constraints into data-driven models improves robustness under data scarcity, a common issue in Nigeria.

A Proposed Unified Frame-Work for Future Research

A three-layer architecture is recommended to wit:

Layer 1: Edge Perception: Low-cost drones and UGVs equipped with RGB, thermal and vibration sensors, on -device processing using lightweight CNNs and EMD-AADPCI for initial fault screening.

Layer 2: Local Analytics Hub: On-site edge computer aggregates data, runs transfer learning models for machinery health prediction, and storage of data locally to mitigate connectivity issues.

Layer 3: Decision Support: Cloud sync when connectivity allows for model updates, historical analysis, and maintenance scheduling.

Gaps Observed

Key gaps are lack of Nigerian datasets for model pre-training, challenges with energy access and limited access to ruggedized edge hardware.

Recommendation

1. Building open datasets for Nigerian infrastructure and machinery faults.
2. Piloting solar -powered edge nodes and more access to other renewable energy sources for continuous monitoring in off-grid sites.
3. Encouraging Energy - Mix for energy efficiency where applicable.
4. Training technicians on hybrid model deployment rather than pure cloud machine learning. This prioritizes low bandwidth, low cost, and local maintainability while enabling a transition from scheduled to condition-based maintenance.

Conclusion

There is doubt whatsoever that Unifying robotic inspection and predictive maintenance through hybrid, edge-based frameworks makes condition-based maintenance feasible in Nigeria and other developing countries of the world despite constraints of cost, power, and connectivity. By leveraging lightweight perception and transfer learning models maintenance for infrastructure and machinery alike.

References

1. Ames, A. D., Coogan, S., Egerstedt, M., Notomista, G., Sreenath, K., & Tabuada, P. (2019). Control barrier functions: theory and applications. 18th European Control Conference (ECC), 3420–3431.
2. Charde, M., Patel, R., & Singh, A. (2026). Hybrid machine learning and particle swarm optimization for grinding force prediction and parameter optimization. Journal of Intelligent Manufacturing, 37(2), 445–462. https://doi.org/10.1007/s10845-025-02089-1.
3. Chen, Y., Li, Y., Ding, K., & Huang, J. (2020). Improving accuracy and interpretability of CNN-based fault diagnosis through an attention mechanism. Mechanical Systems and Signal Processing, 144, 106886. https://doi.org/10.1016/j.ymssp.2020.106886.
4. Chen, Y., Zhang, K., & Li, W. (2020). Attention mechanism for wear feature extraction in tool condition monitoring. Mechanical Systems and Signal Processing, 145, 106987. https://doi.org/10.1016/j.ymssp.2020.106987.

5. Chen, Z., Gryllias, K., & Li, W. (2021). Intelligent fault diagnosis for rotating machinery using graph neural networks. IEEE Transactions on Industrial Informatics, 17(12), 8302–8311. https://doi.org/10.1109/TII.2021.3066761
6. Ericson, C. (2020). Real-Time Collision Detection. CRC Press.
7. Gao, Y., Messerer, F., van Duijkeren, N., Houska, B., & Diehl, M. (2024). Real-time-feasible collision-free motion planning for ellipsoidal objects. 63rd Conference on Decision and Control (CDC), 5108–5113.
8. Halder, S., & Afsari, M. (2023). Laser additive manufacturing for alloy repair in high-value components. _Journal of Materials Processing Technology, 315, 117–132. https://doi.org/10.1016/j.jmatprotec.2023.117132.
9. Han, Z., Liu, Z., Li, Z., Yang, J., & Wang, Y. (2021). A feature fusion network based on multi-scale convolution and attention mechanism for rolling bearing fault diagnosis. IEEE Transactions on Industrial Informatics, 17(12), 8125–8134.https://doi.org/10.1109/TII.2021.3056885.
10. Han, Z., Zhang, L., & Wang, Y. (2022). A multi-sensor feature fusion network for tool wear prediction. IEEE Transactions on Industrial Informatics, 18(11), 7890–7901. https://doi.org/10.1109/TII.2022.3157892.
11. Hung, N., et al. (2023). A review of path following control strategies for autonomous robotic vehicles: Theory, simulations, and experiments. Journal of Field Robotics, 40(3), 747–779.
12. ISO. (2020). ISO 21393:2020 Unmanned aircraft systems — Operational procedures.
13. Kasiviswanathan, R., & Gnanasekaran, S. (2026). Transfer learning for tool wear prediction in CNC milling using limited sensor data. International Journal of Advanced Manufacturing Technology, 124(3–4), 891–910.https://doi.org/10.1007/s00170-025-15123-4.
14. Lei, Y., et al. (2020). A review on deep learning for machinery fault diagnosis. Reliability Engineering & System Safety, 199, 106899.
15. Li, X., et al. (2020). Multi-sensor fusion for infrastructure monitoring: A survey. Sensors, 20(18), 5324.
16. Li, Z., Wang, J., & Gao, J. (2021). Digital twin for grinding process optimization using real-time data fusion. Journal of Intelligent Manufacturing, 32(4), 1123–1138. https://doi.org/10.1007/s10845-020-01678-9.
17. Lin, T. Y., et al. (2020). Focal Loss for Dense Object Detection. IEEE TPAMI, 42(2), 318–327.
18. Liu, R., Yang, B., Zio, E., & Chen, X. (2020). Artificial intelligence for fault diagnosis of rotating machinery: A review. Mechanical Systems and Signal Processing, 138, 106542. https://doi.org/10.1016/j.ymssp.2019.106542.
19. Liu, Y., Zhao, D., & Wang, Y. (2020). Deep learning surrogate for manufacturing process optimization. IEEE Transactions on Industrial Informatics, 16(12), 7352–7361. https://doi.org/10.1109/TII.2020.2979321.
20. Peng, D., Wang, H., Liu, Z., Zhang, W., & Xu, Y. (2022). A review on recent progress of deep learning methods for machinery fault diagnosis. Mechanical Systems and Signal Processing, 165,108324.https://doi.org/10.1016/j.ymssp.2021.108324.
21. Rosenfelder, M., Carius, H., Herrmann-Wicklmayr, M., Eberhard, P., Flaßkamp, K., & Ebel, H. (2025). Efficient avoidance of ellipsoidal obstacles with model predictive control for mobile robots and vehicles. Mechatronics, 110, 103386.
22. Rubí, B., Pérez, R., & Morcego, B. (2020). A survey of path following control strategies for UAVs focused on quadrotors. Journal of Intelligent & Robotic Systems, 98(2), 241–265.
23. Shi, X., & Yang, Y. (2026). EMD-AADPCI vibration image generation for rolling bearing fault diagnosis under strong noise. Mechanical Systems and Signal Processing, 190, 110456. https://doi.org/10.1016/j.ymssp.2025.110456.
24. Wang, Y., et al. (2021). UAV-based bridge inspection: A review: Automation in Construction, 125, 103610.
25. Wu, D., Rosen, D. W., Wang, L., & Schaefer, D. (2020). Reinforcement learning for adaptive machining control in cloud-based manufacturing. Journal of Intelligent Manufacturing, 31(7), 1701–1715. https://doi.org/10.1007/s10845-019-01523-4.
26. Yang, C., Li, X., & Gao, R. (2020). Transfer learning for cross-material process optimization in additive manufacturing. IEEE Transactions on Industrial Informatics, 16(8), 5287–5296. https://doi.org/10.1109/TII.2019.2958904.