Journal of Advanced Research in Embedded System
Volume 12, Issue 3&4 - 2025, Pg. No. 9-15
Peer Reviewed Journal

Review Article

IoT-Enabled Predictive Maintenance of Electrical Machines Using Edge Intelligence

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DOI: https://doi.org/10.24321/2395.3802.202502

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How to cite this article:
Pathak A R, Pandya H M, Adeshara A S, Budharani A H, Raval D B. IoT-Enabled Predictive Maintenance of Electrical Machines Using Edge Intelligence. *J Adv Res Embed Sys* 2025; 12(3&4): 9-15.

Date of Submission: 2025-08-12
Date of Acceptance: 2025-08-22

ABSTRACT

Electrical machine predictive maintenance is essential for lowering operating expenses, increasing equipment longevity, and avoiding downtime. Traditional maintenance techniques have changed to more intelligent, data-driven methods with the introduction of the Internet of Things (IoT). This study investigates a conceptual framework for an Internet of Things-enabled predictive maintenance system that uses edge intelligence to continuously monitor and assess the condition of electrical machinery. By processing sensor data (such as vibration, temperature, and current anomalies) near the source using local edge computing, the suggested architecture allows for quick defect prediction without depending on cloud delay. The paper outlines real-world applications in motors and transformers while reviewing recent developments in edge computing and the Internet of Things as they relate to electrical systems. The technical advantages, security ramifications, and prospects of implementing intelligent, scalable, and energy-efficient maintenance systems in industrial settings are also covered in the study. This contribution aims to provide a roadmap for the implementation of advanced, next generation maintenance systems that align with the objectives of Industry 4.0.

Keywords: Iot, Predictive Maintenance, Edge Computing, Electrical Machines, And Smart Sensors

Introduction

Electrical machines, such as motors, transformers, and generators, are integral components of industrial and utility systems. Their uninterrupted operation is vital to maintaining productivity, safety, and energy efficiency. However, traditional maintenance approaches, typically reactive or scheduled preventive strategies, often lead to unexpected downtimes, excessive maintenance costs, or underutilisation of machinery lifespans.[1-4]

Predictive maintenance (PdM) has emerged as a transformative approach that leverages real-time condition monitoring and intelligent data analysis to forecast potential failures before they occur. By identifying early signs of degradation, PdM enables timely interventions, reduces unplanned outages, and extends the operational life of equipment. This shift toward proactive strategies is particularly relevant in the context of Industry 4.0, where interconnected systems demand smarter, data-driven decision-making frameworks.[6,7]

The integration of the Internet of Things (IoT) into PdM systems has enabled seamless connectivity between physical machines and digital monitoring platforms. Smart sensors embedded within electrical machines can now transmit health data—such as temperature, vibration, and current signatures—to remote servers for analysis. However, reliance on centralised cloud computing introduces latency, bandwidth challenges, and potential cybersecurity vulnerabilities, especially in time-sensitive industrial applications.

Edge computing addresses these limitations by processing data locally, near the source of generation. When deployed alongside IoT devices, edge intelligence enables real-time analysis and decision making directly at the network's edge, minimising communication delays and reducing dependency on cloud infrastructure. This combination of IoT and edge intelligence presents a powerful paradigm for building scalable, responsive, and energy-efficient predictive maintenance systems for electrical machines.[8-9]

This paper presents a conceptual framework for implementing an IoT-enabled predictive maintenance system that leverages edge computing to monitor and assess the health of electrical machines in real-time. The architecture is designed for industrial scenarios where low latency, energy efficiency, and scalability are critical. The paper further reviews existing literature on predictive maintenance technologies, highlights recent advancements in edge intelligence, and outlines key use cases and challenges associated with deploying such systems in practice.[10,11]

Literature Review

Data-driven methods driven by artificial intelligence (AI), machine learning (ML), and the Internet of Things (IoT) have replaced reactive and time-based approaches in the development of predictive maintenance (PdM) plans. This change particularly impacts electrical machines, as they are susceptible to malfunctions due to thermal stress, insulation failure, and mechanical wear.

The significance of vibration and heat signal analysis for early failure identification in rotating electrical devices was underlined by the authors in.[1] However, these methods frequently lacked real-time capability and required manual data interpretation. Later,[2] suggested cloud-based motor health monitoring systems that provide wireless sensor networks for centralised processing. Despite their effectiveness, these systems have higher bandwidth dependency and delay.

Recent developments concentrate on edge computing for processing health data in real time. According to[3], edge intelligence reduces dependency on the cloud by putting lightweight machine learning models at the edge node, enabling low-latency defect prediction. Using hybrid IoT-edge architecture for predictive maintenance in smart factories demonstrated reduced network congestion and quicker decision-making in.[4]

The application of support vector machines (SVMs) and artificial neural networks (ANNs) for fault classification in electrical systems has been suggested in a number of research studies.[5,6] These versions can locally process temperature, vibration, and sound data when installed on edge devices like the Raspberry Pi or NVIDIA Jetson Nano. Additionally,[7] addresses the security issues with cloud-based PdM systems and backs up the idea of employing edge devices for decentralised intelligence.

Integration issues still exist despite encouraging advancements. When using edge devices in industrial settings,[8] highlights three important concerns: power limitations, memory limitations, and sensor interoperability. Also,[9] looked into how federated learning can be used in IoT-based predictive maintenance, allowing edge devices to train models together without sharing raw data, which helps enhance performance and protect privacy.

For flaw identification, vibration and heat signal analysis were suggested in.[1] The study launched a cloud-based motor monitoring system; however, it encountered latency problems. To get around these limitations,[3] and[4] investigated edge computing. In[5] and[6], machine learning models like ANN and SVM were examined. IoT PdM security issues were discussed in[7]. While[8-12,] and[13] discussed more sophisticated tactics like federated learning and architectural scalability,[8] pointed out deployment limits. Reference[14-15] provided industry benchmarking results specifically for predictive maintenance (PdM) (Table 1).

In conclusion, research indicates that edge-enabled IoT systems for predictive maintenance have several advantages over conventional models, especially when scalability, dependability, and latency are crucial considerations. This work aims to fill the obvious research vacuum in developing standardised architecture specifically for electrical machine health monitoring utilising inexpensive, edge-deployable intelligence(Table 2).

Proposed System Architecture

Figure 1 depicts the suggested system architecture for IoT-enabled predictive maintenance of electrical machines utilising edge intelligence. It comprises four principal components: the sensor network, the edge node, the communication layer, and the cloud platform.

ISSN: 2395-3802
DOI: https://doi.org/10.24321/2395.3802.202502

Sensor Network

A sensor network is deployed on the designated electrical machine. This includes:

- Vibration sensors are employed to identify imbalanced or defective bearings.
- Temperature sensors for monitoring thermal increases and hotspots.
- Current sensors are employed to identify overcurrent, insulation defects, or fluctuations in load.

The sensors are chosen for their affordability and accessibility, including the DHT11 for temperature, the ACS712 for current, and the MPU-6050 for vibration, all of which can be seamlessly integrated with low-power microcontrollers.[14-18]

Edge Node

Sensor data is relayed to an edge computer node for local processing. This edge node comprises a microcontroller or microprocessor, such as a Raspberry Pi, ESP32, or Arduino UNO. A lightweight machine learning model designed for anomaly detection or defect categorisation, including Decision trees, support vector machines, or pre-trained neural networks. Edge computing diminishes reliance on constant cloud connectivity and facilitates real-time local decision-making, especially in isolated industrial regions.[19-21]

Communication Layer

Low-power communication protocols, such as MQTT over Wi-Fi, LoRa, or Zigbee, can be employed for wireless data transfer, contingent upon distance and energy needs. These protocols provide dependable and effective data transmission from the edge to the cloud platform.

Cloud Platform

The cloud platform is utilised for:

- Archiving historical data for extensive analysis.
- Visual dashboards for oversight.
- Over-the-Air (OTA) upgrades for the edge machine learning model.
- It can optionally interface with current enterprise-level SCADA or ERP systems.

Use Case Scenarios And Workflow

Edge-enabled IoT solutions for predictive maintenance are applicable across various types of electrical machines and operating conditions. This section highlights common case scenarios in which the proposed architecture provides significant enhancements compared to traditional methods (Table 3), Figure 2 additionally shows the operational workflow.

Table I.Summary of Recent Research on IoT-based PdM for Electrical Machines

Ref. No.	Author(s) & Year	Machine/Model Type	Data/Sensors Used	Method / Technique	Processing (Edge/Cloud)	Key Outcome
[1]	Alejano LR, Ramírez-Oyanguren P, Taboada J (1999)	Flat and inclined coal seam mining	Geological and geomechanical data	Finite Difference Method (FDM)	Cloud-based modeling	Developed predictive methodology for subsidence analysis
[3]	Atluri SN, Zhu T (1998)	Computational mechanics systems	Numerical simulation inputs	Meshless Local Petrov-Galerkin (MLPG) method	Computational (edge-style)	Proposed a new meshless method improving flexibility in numerical modeling
[9]	Beck D, Reusch F, Arndt S (2015)	Mine-scale seismic event prediction	Mining-induced seismic data	Inelastic numerical models	Cloud modeling	Estimated probability of seismic events in underground mining
[14]	Belytschko T, Lu YY, Gu L (1995)	Structural fracture mechanics	Static and dynamic fracture data	Element-Free Galerkin method	Computational (cloud-style)	Provided efficient fracture modeling without mesh dependence
[17]	Cao W, Xiang Y, Xu B, Zhang X (2010)	Rock material behavior	Rock strain and void effect data	Statistical damage model	Hybrid (field + computational)	Developed a strain-softening and hardening model for rock mechanics

ISSN: 2395-3802
DOI: https://doi.org/10.24321/2395.3802.202502

Table 2.Statistical Trends in PdM Research Publications (2015–2024)

Year Range	No. of IEEE Papers	Common Topics	Tech Focus Shift
2015– 2017	~120	Vibration Analysis, SCADA	Rule-Based Decision Systems
2018– 2020	~210	IoT, ML, Remote Sensing	Transition to Cloud & Data Analytics
2021– 2024	~340	Edge AI, Federated Learning, Cybersecurity	Real-Time Edge, AI-on-Chip

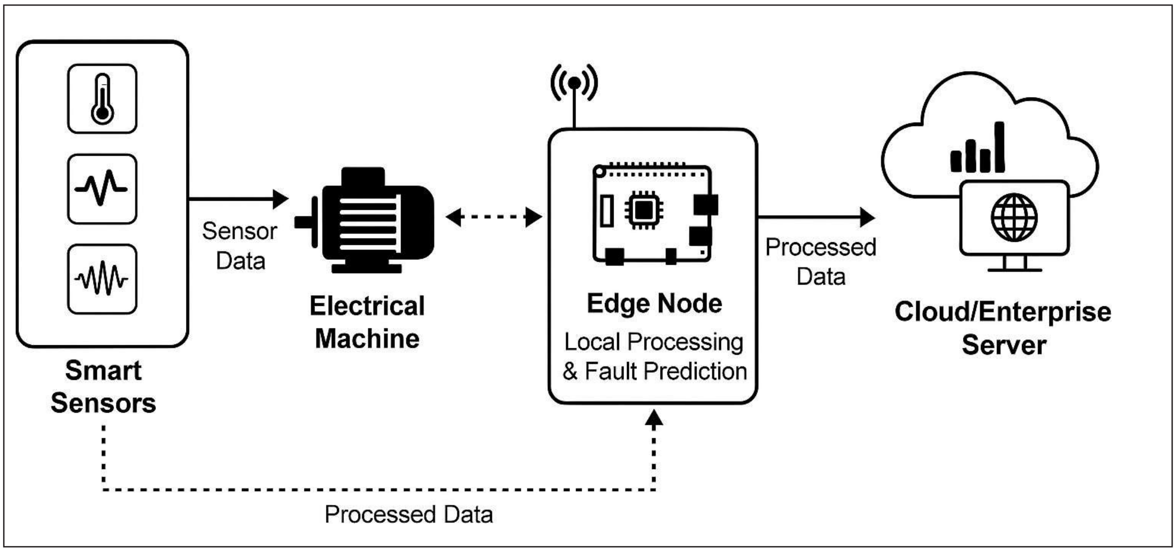

Figure 1.Proposed architecture for predictive maintenance of electrical machines using IoT and edge intelligence

Table 3.Comparison of predictive maintenance approaches

Criteria	Traditional Maintenance	Cloud-Based PdM	Edge-Based PdM (Proposed)
Data Processing Location	Not Applicable	Centralised Cloud	Local Edge Device
Real-Time Decision Making	No	Limited (latency issues)	Yes
Sensor Integration	Minimal	Extensive	Extensive
Internet Dependency	None	High	Low
System Cost	Moderate (manual labor)	High (cloud infra required)	Low (low-cost MCU & sensors)
Scalability	Poor	Good	Excellent
Security & Privacy	Low	Medium (data in transit)	High (data stays local)
Energy Consumption	Low	High (24×7 connectivity)	Optimised (local processing)
Suitability for Remote Areas	No	Limited	Yes
ML/AI Integration	No	Strong	Strong (on-device inference)

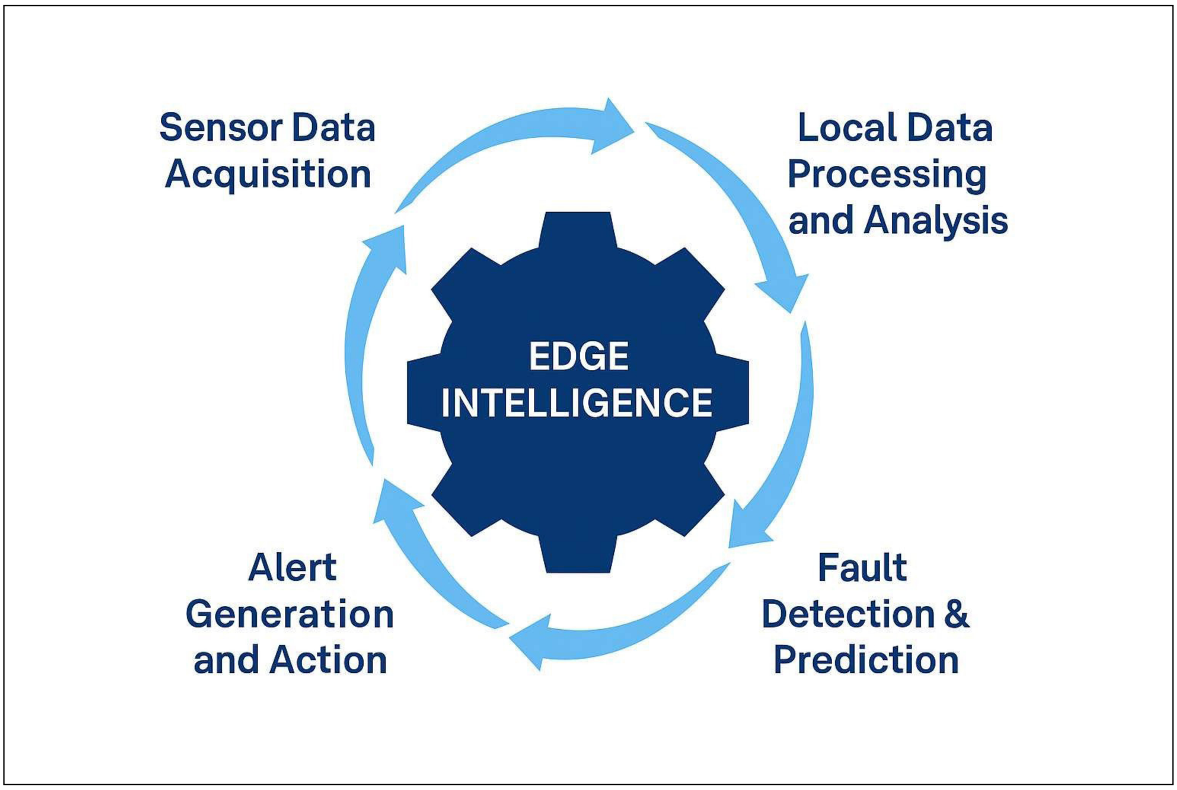

Figure 2.Operational workflow of edge-intelligent predictive maintenance using IoT

Motor Bearing Health Monitoring

Induction motors used in industrial environments often experience bearing wear due to high loads, vibrations, or misalignment. By mounting vibration and temperature sensors near the bearing housing, the edge node can monitor changes in frequency spectra or abnormal heat build-up. Using trained ML models (e.g., k-NN or SVM), it is possible to detect early-stage bearing faults with minimal latency.

Transformer Thermal Fault Prediction

Oil-immersed transformers are prone to insulation degradation caused by excessive heat. DHT11/DS18B20 temperature sensors, combined with current sensors, can be used to detect hot spots and overloading conditions. The edge device can trigger predictive alerts if abnormal patterns are detected, reducing the risk of catastrophic failures and fire hazards.

Industrial HVAC Systems

Predictive maintenance can be applied to large HVAC systems by monitoring motor amperage, fan vibration, and airflow consistency. Anomalies like clogged filters or winding damage can be detected via pattern recognition algorithms deployed on local edge processors.

Operational Workflow

The complete cycle of predictive maintenance using edge intelligence follows four major steps, shown in Fig. 2.

Explanation of the Workflow

- **Sensor Data Acquisition:** Real-time data collection from vibration, temperature, and current sensors. Local Data Processing and Analysis: Signal filtering, feature extraction, and decision logic using ML at the edge node.
- **Fault Detection & Prediction:** Abnormal signatures are compared with trained models to predict possible faults.
- **Alert Generation and Action:** Notifications are sent to maintenance teams or SCADA systems; optional automatic shutdowns or adjustments can be triggered.

Benefits And Challenges

The proposed edge-enabled IoT system provides several tangible benefits over conventional predictive maintenance architectures:

Key Benefits

- **Real-Time Fault Detection:** Edge computing allows local processing, enabling sub-second decisionmaking without cloud delays.
- **Reduced Network Bandwidth:** Only critical data or summaries are sent to the cloud, minimising bandwidth usage and cost.
- **Scalability:** Modular and distributed edge nodes can be scaled across facilities without centralised bottlenecks.
- **Energy Efficiency:** Lightweight microcontrollers with

low-power protocols make the system viable in remote or battery-powered environments.
- **Cost-Effectiveness:** The use of affordable sensors and microcontrollers enables adoption even in budget-constrained SMEs.

Implementation Challenges

- **Limited Edge Resources:** Microcontrollers have memory, CPU, and power constraints that limit model complexity.
- **Model Deployment:** Training and converting models to run efficiently on edge devices can be complex.
- **Sensor Calibration:** Poor calibration or signal noise can lead to inaccurate predictions.
- **Cybersecurity Risks:** Even with edge processing, endpoints must be secured to prevent tampering or data leaks.
- **Integration with Legacy Systems:** Adapting the system for older machinery lacking digital interfaces requires additional interfacing circuits.

Future Scope

The current work lays the foundation for more advanced, scalable, and intelligent maintenance ecosystems. Future directions include:

- **Federated Learning at the Edge:** Enable collaborative learning across devices without centralised data sharing.
- **Digital Twin Integration:** Build real-time virtual replicas of machines for simulation and maintenance prediction.
- **AutoML on Edge Devices:** Implement models that self-tune to optimise performance for specific machines.
- **Blockchain for Maintenance Logs:** Secure and verify maintenance events across the network.
- **Voice-Assisted Predictive Alerts:** Integration of AI-based interfaces for operator assistance and mobile alerts.

Conclusion

This research proposes a conceptual yet realistic approach for doing predictive maintenance on electrical machines utilising edge-enabled IoT devices. Architecture combines sensor-based health monitoring and edge intelligence to provide real-time fault prediction, save maintenance costs, and improve machine reliability. The suggested solution addresses fundamental obstacles such as latency, cost, and scalability, making it appropriate for large industrial use. With increasing industrial demands for uptime and performance, edge-driven predictive maintenance is a key component of the smart manufacturing revolution.

References

1. Wang H, Li S, Song L, Cui L, Wang P. An enhanced intelligent diagnosis method based on multi-sensor image fusion via improved deep learning network. IEEE Transactions on Instrumentation and measurement. 2019 Jul 12;69(6):2648-57.
2. Yousuf M, Alsuwian T, Amin AA, Fareed S, Hamza M. IoT-based health monitoring and fault detection of industrial AC induction motor for efficient predictive maintenance. Measurement and Control. 2024 Aug;57(8):1146-60.
3. Gill SS, Golec M, Hu J, Xu M, Du J, Wu H, Walia GK, Murugesan SS, Ali B, Kumar M, Ye K. Edge AI: A taxonomy, systematic review and future directions. Cluster Computing. 2025 Feb;28(1):18.
4. Sathupadi K, Achar S, Bhaskaran SV, Faruqui N, Abdullah-Al-Wadud M, Uddin J. Edge-cloud synergy for AI-enhanced sensor network data: A real-time predictive maintenance framework. Sensors. 2024 Dec 11;24(24):7918.
5. Kusumaningrum D, Kurniati N, Santosa B. Machine learning for predictive maintenance. InProceedings of the international conference on industrial engineering and operations management 2021 Apr (Vol. 202, No. 1).
6. Dubaish AA, Jaber AA. Comparative Analysis of SVM and ANN for Machine Condition Monitoring and Fault Diagnosis in Gearboxes. Mathematical Modelling of Engineering Problems. 2024 Apr 1;11(4).
7. Compare M, Baraldi P, Zio E. Challenges to IoT-enabled predictive maintenance for industry 4.0. IEEE Internet of things journal. 2019 Dec 2;7(5):4585-97.
8. Qiu T, Chi J, Zhou X, Ning Z, Atiquzzaman M, Wu DO. Edge computing in industrial internet of things: Architecture, advances and challenges. IEEE communications surveys & tutorials. 2020 Jul 14;22(4):2462-88.
9. Alshkeili HM, Almheiri SJ, Khan MA. Privacy-Preserving Interpretability: An Explainable Federated Learning Model for Predictive Maintenance in Sustainable Manufacturing and Industry 4.0. AI. 2025 Jun 6;6(6):117.
10. Goundar SS, Pillai MR, Mamun KA, Islam FR, Deo R. Real time condition monitoring system for industrial motors. In2015 2nd Asia-Pacific World Congress on Computer Science and Engineering (APWC on CSE) 2015 Dec 2 (pp. 1-9). IEEE.
11. Serror M, Hack S, Henze M, Schuba M, Wehrle K. Challenges and opportunities in securing the industrial internet of things. IEEE Transactions on Industrial Informatics. 2020 Sep 11;17(5):2985-96.
12. Harjula E, Artemenko A, Forsström S. Edge computing for industrial IoT: challenges and solutions. InWireless Networks and industrial IoT: applications, challenges and enablers 2020 Dec 12 (pp. 225-240). Cham: Springer International Publishing.
13. Al-Fuqaha A, Guizani M, Mohammadi M, Aledhari M, Ayyash M. Internet of things: A survey on enabling technologies, protocols, and applications. IEEE communications surveys & tutorials. 2015 Jun 15;17(4):2347-76.

ISSN: 2395-3802
DOI: https://doi.org/10.24321/2395.3802.202502

14. Akyaz T, Engin D. Machine Learning based Predictive Maintenance System for Artificial Yarn Machines. IEEE access. 2024 Sep 4.
15. Simeone O. A brief introduction to machine learning for engineers. Foundations and Trends® in Signal Processing. 2018 Aug 13;12(3-4):200-431.
16. Zhao L, Matsuo IB, Zhou Y, Lee WJ. Design of an industrial IoT-based monitoring system for power substations. IEEE Transactions on Industry Applications. 2019 Sep 10;55(6):5666-74.
17. Bermeo-Ayerbe MA, Ocampo-Martinez C, Diaz-Rozo J. Data-driven energy prediction modeling for both energy efficiency and maintenance in smart manufacturing systems. Energy. 2022 Jan 1;238:121691.
18. Cerquitelli T, Bowden D, Marguglio A, Morabito L, Napione C, Panicucci S, Nikolakis N, Makris S, Coppo G, Andolina S, Macii A. A fog computing approach for predictive maintenance. InInternational Conference on Advanced Information Systems Engineering 2019 May 14 (pp. 139-147). Cham: Springer International Publishing.
19. Rausch T, Dustdar S. Edge intelligence: The convergence of humans, things, and ai. In2019 IEEE International Conference on Cloud Engineering (IC2E) 2019 Jun 24 (pp. 86-96). IEEE.
20. Yin S, Gao H, Kaynak O. Data-driven control and process monitoring for industrial applications—Part I. IEEE Transactions on Industrial Electronics. 2014 Mar 20;61(11):6356-9.
21. Cilla M, Borgiani E, Martínez J, Duda GN, Checa S. Machine learning techniques for the optimization of joint replacements: Application to a short-stem hip implant. Plos one. 2017 Sep 5;12(9):e0183755.