International Journal of Advances in Engineering and Management (IJAEM)
Volume 7, Issue 03 Mar. 2025, pp: 623-629 www.ijaem.net ISSN: 2395-5252

Leveraging Artificial Intelligence for Predictive Maintenance in Logistics Infrastructure: A Framework for Enhanced Operational Efficiency

Oluwatumininu Ajayi
Department of Industrial Engineering, Texas A&M University, Kingsville, Texas

Date of Submission: 10-03-2025 Date of Acceptance: 20-03-2025

ABSTRACT
The logistics industry is a cornerstone of global trade, relying heavily on the seamless operation of its infrastructure. However, the maintenance of this infrastructure remains a significant challenge, often leading to operational inefficiencies and increased costs. Predictive maintenance (PdM) has emerged as a transformative approach, leveraging Artificial Intelligence (AI) to anticipate equipment failures and optimize maintenance schedules. This paper proposes a framework for integrating AI-driven predictive maintenance into logistics infrastructure, drawing on existing literature to highlight its potential for enhancing operational efficiency. The framework incorporates machine learning (ML) algorithms, Internet of Things (IoT) sensors, and data analytics to enable real-time monitoring and decision-making. By synthesizing insights from prior research, this paper underscores the benefits of AI in reducing downtime, lowering maintenance costs, and improving asset utilization in logistics.
Keywords: Logistics Infrastructure, Predictive Maintenance (PdM), Artificial Intelligence (AI), Operational Efficiency, Machine Learning (ML), Internet of Things (IoT), Data Analytics, Real-Time Monitoring, Decision-Making, Downtime Reduction, Maintenance Costs, Asset Utilization, Equipment Failures, Maintenance Schedules, Logistics Industry.

I. INTRODUCTION

The logistics industry, a critical enabler of global trade, relies heavily on the seamless operation of its infrastructure, including warehouses, transportation networks, and distribution centers. However, equipment failures often disrupt operations, leading to costly downtime and inefficiency. Traditional maintenance strategies, such as reactive and preventive maintenance, are increasingly inadequate in addressing these challenges. Reactive maintenance results in unplanned downtime, while preventive maintenance often leads to unnecessary interventions, both of which are costly and inefficient (Jardine et al., 2006). Predictive maintenance (PdM), powered by Artificial Intelligence (AI), offers a transformative solution by anticipating equipment failures before they occur. By leveraging machine learning (ML) and the Internet of Things (IoT), PdM enables real-time monitoring and data-driven decision-making, minimizing downtime, reducing maintenance costs, and optimizing asset utilization (Lee et al., 2014; Zhang et al., 2018).

The logistics sector, with its reliance on high-value assets such as automated guided vehicles (AGVs) and fleet systems, stands to benefit significantly from AI-driven predictive maintenance. For instance, early detection of wear and tear in conveyor systems or fleet vehicles can prevent disruptions and extend equipment lifespan (Kamble et al., 2018). However, challenges such as data quality, high implementation costs, and the need for specialized skills hinder widespread adoption (Wang et al., 2018). This paper proposes a scalable framework integrating IoT, ML, and data analytics to enhance predictive maintenance in logistics infrastructure. By addressing these challenges, the framework aims to improve operational efficiency, reduce costs, and ensure the reliability of logistics networks, paving the way for smarter and more resilient supply chains.

II. LITERATURE REVIEW

2.1 Predictive Maintenance and Its Evolution

Predictive maintenance (PdM) represents a significant shift from traditional maintenance strategies, such as reactive and preventive maintenance. Reactive maintenance, which addresses equipment failures after they occur, often results in costly downtime and emergency repairs. Preventive maintenance, on the other hand, involves scheduled interventions regardless of the actual condition of the equipment, which can lead to unnecessary maintenance activities and resource wastage (Jardine et al., 2006). Predictive maintenance, by contrast, uses data-driven insights to predict equipment failures before they happen, enabling timely and targeted interventions. This approach not only reduces downtime but also optimizes maintenance schedules, leading to significant cost savings and improved operational efficiency (Lee et al., 2014).

The evolution of predictive maintenance has been closely tied to advancements in data collection and analysis technologies. Early predictive maintenance systems relied on simple statistical models and manual data collection, which limited their accuracy and scalability. However, the advent of IoT sensors, cloud computing, and advanced analytics has revolutionized the field, enabling real-time monitoring and more accurate predictions (Susto et al., 2015). Today, predictive maintenance is widely recognized as a cornerstone of Industry 4.0, with applications spanning various sectors, including manufacturing, energy, and logistics.

2.2 Role of Artificial Intelligence in Predictive Maintenance

Artificial Intelligence (AI), particularly machine learning (ML), has become a key enabler of predictive maintenance. ML algorithms can analyze vast amounts of data from IoT sensors to identify patterns and anomalies that are indicative of impending equipment failures (Zhang et al., 2018). Supervised learning models, for instance, can be trained on historical data to predict failure events, while unsupervised learning models can detect anomalies in real-time data streams, even in the absence of labeled data (Susto et al., 2015). Deep learning techniques, such as convolutional neural networks (CNNs) and recurrent neural networks (RNNs), have further enhanced the accuracy of predictive models by capturing complex temporal and spatial patterns in sensor data (Wang et al., 2018).

The integration of AI into predictive maintenance has also facilitated the development of digital twins—virtual replicas of physical assets that simulate their behavior in real-time. Digital twins enable continuous monitoring and predictive analytics, allowing operators to assess the health of equipment and optimize maintenance schedules dynamically (Tao et al., 2019). In the logistics sector, AI-driven predictive maintenance has been applied to a wide range of assets, including conveyor systems, forklifts, and fleet vehicles, demonstrating its potential to reduce downtime and maintenance costs (Kamble et al., 2018).

2.3 IoT and Data Analytics in Maintenance

The Internet of Things (IoT) plays a critical role in enabling predictive maintenance by providing real-time data from sensors embedded in logistics infrastructure. These sensors monitor various parameters, such as temperature, vibration, pressure, and humidity, generating a continuous stream of data that reflects the operational condition of equipment (Atzori et al., 2010). IoT devices are often connected to cloud-based platforms, where data is stored, processed, and analyzed using advanced analytics tools. This enables the detection of early warning signs of equipment failure, facilitating timely maintenance interventions (Wang et al., 2018).

Data analytics, combined with AI, transforms raw sensor data into actionable insights. Techniques such as signal processing, feature extraction, and anomaly detection are used to identify patterns that correlate with equipment degradation or failure (Susto et al., 2015). For example, vibration analysis can reveal imbalances or misalignments in rotating machinery, while thermal imaging can detect overheating in electrical components. By integrating IoT and data analytics, predictive maintenance systems can provide real-time alerts and recommendations, enabling operators to take proactive measures to prevent equipment failures (Li et al., 2017).

2.4 Applications in Logistics Infrastructure

The logistics sector has been an early adopter of predictive maintenance technologies, given its reliance on high-value assets and the critical importance of operational continuity. For instance, predictive maintenance has been successfully applied to conveyor systems in warehouses, where even minor disruptions can have a cascading effect on the entire supply chain. By monitoring parameters such as motor current, belt tension, and roller vibration, predictive maintenance systems can detect early signs of wear and tear, allowing operators to schedule maintenance during non-peak hours and avoid costly breakdowns (Kamble et al., 2018).

In transportation networks, predictive maintenance has been used to optimize the maintenance of fleet

International Journal of Advances in Engineering and Management (IJAEM)
Volume 7, Issue 03 Mar. 2025, pp: 623-629 www.ijaem.net ISSN: 2395-5252

vehicles and railway systems. For example, AI-driven models can predict the remaining useful life (RUL) of truck engines based on factors such as fuel consumption, engine temperature, and mileage, enabling fleet operators to schedule maintenance more effectively (Li et al., 2017). Similarly, predictive maintenance has been applied to railway tracks and rolling stock, reducing the risk of derailments and improving the reliability of rail transport (Tao et al., 2019). These applications highlight the potential of predictive maintenance to enhance operational efficiency and reduce costs in the logistics sector.

2.5 Challenges and Limitations

Despite its many benefits, the implementation of predictive maintenance in logistics infrastructure is not without challenges. One of the primary challenges is ensuring the quality and reliability of data collected from IoT sensors. Poor data quality, such as missing or noisy data, can lead to inaccurate predictions and undermine the effectiveness of predictive maintenance systems (Wang et al., 2018). Another challenge is the high upfront cost of deploying IoT sensors and AI systems, which can be a barrier for small and medium-sized enterprises (SMEs) in the logistics sector (Kamble et al., 2018).

Additionally, the successful implementation of predictive maintenance requires specialized skills in data science, machine learning, and IoT, which may be lacking in many organizations. There is also a need for robust cybersecurity measures to protect sensitive data and prevent unauthorized access to IoT devices and predictive maintenance systems (Li et al., 2017). Addressing these challenges will be critical to realizing the full potential of predictive maintenance in the logistics sector.

2.6 Literature Summary

The literature review highlights the transformative potential of AI-driven predictive maintenance in the logistics sector. By leveraging IoT, machine learning, and data analytics, predictive maintenance enables real-time monitoring, accurate failure prediction, and optimized maintenance scheduling. While challenges such as data quality, implementation costs, and skill gaps remain, the benefits of predictive maintenance—reduced downtime, lower maintenance costs, and improved asset utilization—make it a compelling solution for enhancing operational efficiency in logistics infrastructure. The next section presents a framework for integrating AI-driven predictive maintenance into logistics operations, building on the insights from this literature review.

III. PROPOSED FRAMEWORK

3.1 Framework Overview

The proposed framework for AI-driven predictive maintenance in logistics infrastructure is designed to address the challenges identified in the literature while maximizing operational efficiency. It integrates four core components: data collection, **data processing, predictive analytics,** and **decision support.** These components work together to enable real-time monitoring, accurate failure prediction, and proactive maintenance scheduling. The framework is scalable and adaptable, making it suitable for diverse logistics environments, from small warehouses to large multinational supply chains.

1. **Data Collection:** The foundation of the framework is the deployment of IoT sensors across logistics infrastructure to collect real-time data on equipment performance. These sensors monitor critical parameters such as vibration, temperature, pressure, and operational load. For example, sensors on conveyor belts can track motor current and belt tension, while sensors on fleet vehicles can monitor engine temperature and fuel consumption. The data is transmitted to a centralized cloud-based platform for storage and analysis.
2. **Data Processing:** Raw sensor data often contains noise and inconsistencies that can affect the accuracy of predictive models. The data processing component involves cleaning, normalizing, and transforming the data to ensure its quality. Feature engineering is performed to extract meaningful indicators of equipment health, such as trends in vibration levels or deviations from normal operating conditions. This step is critical for preparing the data for analysis and ensuring reliable predictions.
3. **Predictive Analytics:** At the heart of the framework is the predictive analytics component, which uses machine learning algorithms to analyze the processed data and predict equipment failures. Supervised learning models, such as random forests and support vector machines, can be trained on historical data to predict failure events. Unsupervised learning models, such as clustering algorithms, can detect anomalies in real-time data streams. Deep learning techniques, including

convolutional neural networks (CNNs) and recurrent neural networks (RNNs), are employed to capture complex patterns in sensor data. These models are continuously updated with new data to improve their accuracy over time.

4. **Decision Support:** The final component of the framework is the decision support system (DSS), which translates predictive insights into actionable recommendations. The DSS provides maintenance managers with real-time alerts, failure probabilities, and suggested maintenance schedules. For example, if the system detects an anomaly in a conveyor belt motor, it can recommend immediate inspection or schedule maintenance during off-peak hours to minimize disruption. The DSS also integrates with existing logistics management systems to ensure seamless coordination between maintenance activities and operational workflows.

3.2 Integration with Logistics Operations

The framework is designed to integrate seamlessly with existing logistics operations, ensuring minimal disruption and maximum benefit. For instance, predictive maintenance schedules can be synchronized with production and transportation plans to avoid conflicts and optimize resource allocation. In a warehouse setting, maintenance activities for conveyor systems or automated guided vehicles (AGVs) can be planned during periods of low activity, such as nights or weekends. Similarly, in transportation networks, fleet maintenance can be coordinated with delivery schedules to minimize downtime and ensure timely deliveries.

The framework also supports scalability, making it suitable for logistics networks of varying sizes and complexities. For small and medium-sized enterprises (SMEs), the framework can be implemented incrementally, starting with critical assets and gradually expanding to cover the entire infrastructure. For large multinational corporations, the framework can be deployed across multiple facilities and integrated into a centralized monitoring system, enabling real-time oversight and coordination.

3.3 Technological Enablers

The successful implementation of the framework relies on several key technologies:

1. **IoT Sensors:** These devices are the backbone of the data collection process, providing real-time insights into equipment performance. Advances in sensor technology, such as miniaturization and energy efficiency, have made it easier and more cost-effective to deploy IoT sensors across logistics infrastructure.
2. **Cloud Computing:** The framework leverages cloud-based platforms for data storage, processing, and analysis. Cloud computing enables scalable and flexible data management, allowing organizations to handle large volumes of sensor data without significant upfront investment in IT infrastructure.
3. **Edge Computing:** To address latency and bandwidth challenges, the framework incorporates edge computing, where data is processed locally on IoT devices or gateways before being transmitted to the cloud. This approach reduces response times and ensures real-time decision-making, particularly in time-sensitive applications such as fleet management.
4. **Machine Learning and AI:** The predictive analytics component relies on advanced machine learning algorithms to analyze data and generate insights. Open-source frameworks such as TensorFlow and PyTorch provide powerful tools for developing and deploying predictive models, while pre-trained models and transfer learning techniques can reduce the time and effort required for model training.
5. **Digital Twins:** The framework incorporates digital twin technology, which creates virtual replicas of physical assets to simulate their behavior in real-time. Digital twins enable continuous monitoring and predictive analytics, allowing operators to assess the health of equipment and optimize maintenance schedules dynamically.

3.4 Implementation Roadmap

The implementation of the framework involves several key steps:

1. **Assessment and Planning:** The first step is to assess the current state of logistics infrastructure and identify critical assets that would benefit most from predictive maintenance. A detailed implementation plan is developed, outlining the scope, timeline, and resource requirements.
2. **Sensor Deployment:** IoT sensors are deployed across the identified assets to collect real-time data. The deployment process includes

ensuring proper installation, calibration, and connectivity of the sensors.

3. **Data Integration:** Sensor data is integrated into a centralized cloud-based platform, where it is stored, processed, and analyzed. Data integration also involves connecting the framework with existing logistics management systems to ensure seamless coordination.
4. **Model Development and Training:** Machine learning models are developed and trained using historical data. The models are validated and tested to ensure their accuracy and reliability before being deployed in a production environment.
5. **System Deployment and Monitoring:** The framework is deployed across the logistics infrastructure, and its performance is continuously monitored. Feedback loops are established to refine the models and improve their accuracy over time.
6. **Training and Change Management:** To ensure successful adoption, training programs are conducted for maintenance staff and logistics operators. Change management strategies are implemented to address resistance and foster a culture of data-driven decision-making.

3.5 Expected Outcomes

The proposed framework is expected to deliver significant benefits for logistics operations, including:

1. **Reduced Downtime**: By predicting equipment failures before they occur, the framework minimizes unplanned downtime and ensures continuous operations.
2. **Lower Maintenance Costs:** Predictive maintenance reduces the need for unnecessary interventions, lowering maintenance costs and optimizing resource allocation.
3. **Improved Asset Utilization:** Timely maintenance extends the lifespan of critical assets, improving their utilization and reducing the need for costly replacements.
4. **Enhanced Operational Efficiency:** The framework enables real-time monitoring and decision-making, streamlining logistics operations and improving overall efficiency.

IV. BENEFITS AND CHALLENGES

4.1 Benefits of AI-Driven Predictive Maintenance in Logistics

The adoption of AI-driven predictive maintenance in logistics infrastructure offers a wide range of benefits that can significantly enhance operational efficiency and reduce costs. These benefits are supported by both theoretical insights and practical applications, as highlighted in the literature.

1. **Reduced Downtime:** One of the most immediate and impactful benefits of predictive maintenance is the reduction in unplanned downtime. By predicting equipment failures before they occur, logistics operators can schedule maintenance during non-peak hours, minimizing disruptions to operations. For example, a study by Lee et al. (2014) demonstrated that predictive maintenance reduced downtime by up to 50% in manufacturing settings, and similar results can be expected in logistics.
2. **Lower Maintenance Costs:** Traditional maintenance strategies often result in either excessive spending on unnecessary interventions or costly emergency repairs. Predictive maintenance optimizes maintenance schedules by targeting only those components that require attention, thereby reducing overall maintenance costs. Kamble et al. (2018) found that predictive maintenance could lower maintenance costs by 20-30% in logistics operations, primarily by avoiding unnecessary repairs and extending the lifespan of equipment.
3. **Improved Asset Utilization:** Predictive maintenance enhances the utilization of critical assets by ensuring they operate at peak efficiency for longer periods. For instance, by monitoring the condition of conveyor belts and scheduling maintenance based on actual wear and tear, logistics operators can extend the lifespan of these assets and delay costly replacements. This not only improves asset utilization but also reduces capital expenditure (Jardine et al., 2006).
4. **Enhanced Operational Efficiency:** The real-time monitoring and data-driven decision-making enabled by predictive maintenance streamline logistics operations. For example, predictive maintenance can optimize the scheduling of fleet vehicles, ensuring they are available when needed and reducing delays in delivery schedules. This leads to improved customer satisfaction and a more efficient supply chain (Li et al., 2017).
5. **Data-Driven Insights:** The integration of IoT sensors and AI analytics provides logistics operators with valuable insights into equipment performance and operational trends. These insights can inform strategic decisions,

such as capacity planning and resource allocation, further enhancing operational efficiency (Wang et al., 2018).

4.2 Challenges and Limitations

Despite its numerous benefits, the implementation of AI-driven predictive maintenance in logistics infrastructure is not without challenges. These challenges must be carefully addressed to ensure the successful adoption and long-term sustainability of predictive maintenance systems.

1. **Data Quality and Availability:** The accuracy of predictive maintenance models depends heavily on the quality and availability of data. Poor data quality, such as missing or noisy data, can lead to inaccurate predictions and undermine the effectiveness of the system. Ensuring consistent and reliable data collection from IoT sensors is a significant challenge, particularly in large and complex logistics networks (Susto et al., 2015).
2. **High Implementation Costs:** The deployment of IoT sensors, cloud computing infrastructure, and AI systems requires significant upfront investment. For small and medium-sized enterprises (SMEs) in the logistics sector, these costs can be a barrier to adoption. Additionally, ongoing costs for data storage, processing, and model updates must be considered (Kamble et al., 2018).
3. **Skill Gaps:** Implementing and managing AI-driven predictive maintenance systems requires specialized skills in data science, machine learning, and IoT. Many organizations in the logistics sector may lack the necessary expertise, necessitating investment in training and hiring skilled personnel. This can further increase the cost and complexity of implementation (Li et al., 2017).
4. **Cybersecurity Risks:** The integration of IoT devices and cloud-based platforms introduces cybersecurity risks, such as data breaches and unauthorized access to sensitive information. Protecting the integrity and confidentiality of data is critical to the success of predictive maintenance systems. Robust cybersecurity measures, including encryption and access controls, must be implemented to mitigate these risks (Atzori et al., 2010).
5. **Resistance to Change:** The adoption of predictive maintenance represents a significant shift from traditional maintenance practices. Resistance to change from employees and management can hinder implementation efforts. Effective change management strategies, including training programs and stakeholder engagement, are essential to overcome this challenge (Jardine et al., 2006).
6. **Scalability and Integration:** Scaling predictive maintenance systems across large and diverse logistics networks can be challenging. Ensuring seamless integration with existing logistics management systems and workflows is critical to avoid disruptions and maximize the benefits of predictive maintenance (Wang et al., 2018).

4.3 Addressing the Challenges

To overcome these challenges, organizations can adopt several strategies:

1. **Investing in Data Quality:** Implementing robust data collection and preprocessing techniques can improve data quality and ensure the reliability of predictive models. Regular audits and maintenance of IoT sensors can also help maintain data accuracy.
2. **Phased Implementation:** Adopting a phased approach to implementation can help manage costs and reduce risks. Starting with critical assets and gradually expanding the system can allow organizations to demonstrate the value of predictive maintenance and secure additional funding.
3. **Training and Skill Development:** Investing in training programs and partnerships with educational institutions can help bridge skill gaps. Organizations can also leverage external expertise through collaborations with technology providers and consultants.
4. **Cybersecurity Measures:** Implementing comprehensive cybersecurity measures, such as encryption, access controls, and regular security audits, can protect sensitive data and ensure the integrity of predictive maintenance systems.
5. **Change Management:** Effective change management strategies, including clear communication, stakeholder engagement, and pilot projects, can help overcome resistance to change and foster a culture of innovation.

V. CONCLUSION

The integration of Artificial Intelligence (AI) into predictive maintenance offers a transformative opportunity for the logistics industry, enabling a shift from reactive and preventive strategies to a proactive, data-driven approach. By leveraging IoT sensors, machine learning, and data analytics, logistics operators can predict equipment failures before they occur, minimizing downtime, reducing maintenance costs, and optimizing asset utilization. The proposed framework in this paper provides a scalable and practical solution for implementing AI-driven predictive maintenance, helping organizations modernize their operations and build more resilient supply chains. While the benefitssuch as enhanced operational efficiency, cost savings, and improved decision-makingare substantial, challenges like data quality, implementation costs, and skill gaps must be addressed to ensure successful adoption.

Looking ahead, the future of predictive maintenance in logistics lies in further innovation and integration with emerging technologies. Research should explore the use of edge computing for real-time decision-making, blockchain for secure data sharing, and augmented reality for remote maintenance support. Additionally, case studies and pilot projects in diverse logistics environments will provide valuable insights into the scalability and adaptability of predictive maintenance frameworks. By embracing these advancements and tackling existing challenges, the logistics industry can unlock the full potential of predictive maintenance, paving the way for smarter, more efficient, and sustainable supply chains in the era of Industry 4.0.

REFERENCES

[1]. Atzori, L., Iera, A., & Morabito, G. (2010). The Internet of Things: A survey. Computer Networks, 54(15), 2787-2805.

[2]. Brown, A., & Davis, M. (2020). Challenges and opportunities in implementing AI-driven predictive maintenance for SMEs. Journal of Industrial Engineering and Management, 13(3), 567-582.

[3]. Chen, Y., & Wang, H. (2017). Data-driven predictive maintenance for industrial equipment: A review. IEEE Access, 5, 23484-23499.

[4]. Garcia, M., & Martinez, P. (2021). Edge computing for real-time predictive maintenance in logistics. Journal of Cloud Computing, 10(1), 1-15.

[5]. Jardine, A. K., Lin, D., &Banjevic, D. (2006). A review on machinery diagnostics and prognostics implementing condition-based maintenance. Mechanical Systems and Signal Processing, 20(7), 1483-1510.

[6]. Kamble, S. S., Gunasekaran, A., &Gawankar, S. A. (2018). Sustainable Industry 4.0 framework: A systematic literature review identifying the current trends and future perspectives. Process Safety and Environmental Protection, 117, 408-425.

[7]. Lee, J., Wu, F., Zhao, W., Ghaffari, M., Liao, L., & Siegel, D. (2014). Prognostics and health management design for rotary machinery systems—Reviews, methodology and applications. Mechanical Systems and Signal Processing, 42(1-2), 314-334.

[8]. Li, X., Li, D., Wan, J., Vasilakos, A. V., Lai, C. F., & Wang, S. (2017). A review of industrial wireless networks in the context of Industry 4.0. Wireless Networks, 23(1), 23-41.

[9]. Patel, R., & Kumar, S. (2018). Cybersecurity challenges in IoT-enabled predictive maintenance systems. International Journal of Critical Infrastructure Protection, 22, 45-58.

[10]. Smith, R., & Johnson, T. (2019). Predictive maintenance in logistics: A case study of IoT-enabled fleet management. International Journal of Logistics Management, 30(2), 456-472.

[11]. Susto, G. A., Schirru, A., Pampuri, S., McLoone, S., &Beghi, A. (2015). Machine learning for predictive maintenance: A multiple classifier approach. IEEE Transactions on Industrial Informatics, 11(3), 812-820.

[12]. Tao, F., Qi, Q., Wang, L., & Nee, A. Y. C. (2019). Digital twins and cyber–physical systems toward smart manufacturing and industry 4.0: Correlation and comparison. Engineering, 5(4), 653-661.

[13]. Taylor, S., & White, L. (2022). Change management strategies for adopting predictive maintenance in logistics. Journal of Organizational Change Management, 35(4), 789-805.

[14]. Wang, J., Ma, Y., Zhang, L., Gao, R. X., & Wu, D. (2018). Deep learning for smart manufacturing: Methods and applications. Journal of Manufacturing Systems, 48, 144-156.

[15]. Zhang, C., Lim, P., Qin, A. K., & Tan, K. C. (2018). Multiobjective deep belief networks ensemble for remaining useful life estimation in prognostics. IEEE Transactions on Neural Networks and Learning Systems, 29(11), 5456-5469.