International Academic Institute for Science and Technology

International Academic Journal of Science and Engineering
Vol. 11, No. 4, 2024, pp. 10-15.

ISSN 2454-3896

International Academic Journal of Science and Engineering

www.iaiest.com

AI-Based Predictive Maintenance for Industrial IOT Applications

Prakash Kumar [a], Rupal Tiwari [b]

[a] *Department of Civil Engineering, Brick Lane Engineering College, Ajmer.*
[b] *Department of Civil Engineering, Brick Lane Engineering College, Ajmer.*

Abstract

The technologies that are being investigated and used in a wide range of ways across different industry verticals in the twenty-first century include Industrial IoT (Internet of Things-IIoT) and Intelligent Production & Manufacturing. In order to meet the service requirements of advanced manufacturing complex networks and safety-critical infrastructures, this new era demands that, in addition to modernizing industry processes, the strategic importance of sophisticated, intelligent, and effective predictive structural health monitoring and management technologies be increased globally. Real-time machine sensor readings are recorded during the machine monitoring process and shown on a graph with threshold limitations. Natural variation is an essential part of the process, and the measured values that fall within the thresholds show that everything is functioning normally and according to plan. A serious issue that needs to be addressed right away to prevent negative outcomes is indicated if measured values exceed the threshold limits. In the past, manufacturers have used SCADA systems to accomplish PdM, manually hardcoding thresholds and putting in place static alert rules, among other changes. The "Remaining Useful Life (RUL) Estimation" is an additional pillar. It makes predictions about how long a machine will last before requiring repairs or replacement. The automobile, nuclear, pharmaceutical, and aviation industries are just a few of the industries where decision-making may be significantly impacted by an accurate RUL assessment. RUL estimates are frequently calculated using one of two main approaches: data-driven models or model-based models.

Keywords: Intelligent Production, Manufacturing, Industrial IOT, AI.

DOI: 10.71086/IAJSE/V11I4/IAJSE1164
Received: 16 September 2024/Revised: 09 October 2024/Accepted: 19 November 2024/Published: 30 December 2024

Introduction

For anyone hoping to transform the industry's routine processes, Industry 4.0 is undergoing a significant shift. Beginning with steam engines for power generation, assembly lines for mass manufacturing, and ultimately the computer to make the entire process quick and efficient, groundbreaking industrial innovations have transformed the world since the 1800s (Banerjee et al., 2024). Industry 4.0 is rapidly spreading around the world and affecting every industry vertical. The integration of intelligent robotic systems supported by sophisticated algorithms is being propelled by Industry 4.0. It is based on the fundamental ideas of CPS (cyber-physical systems) and IIOT. These computer-assisted methods are used to automate, monitor, and control physical objects including cars, robots, and machinery (Haque et al., 2024). It provides businesses with unmatched information and control by integrating with back-end technologies like enterprise resource planning (ERP). Industry X.0, the next industrial revolution, is quickly coming and aims to create digital value across industrial sectors using a range of next-generation technologies. The development of industrialization toward Industry X.0 is shown in Figure 1.

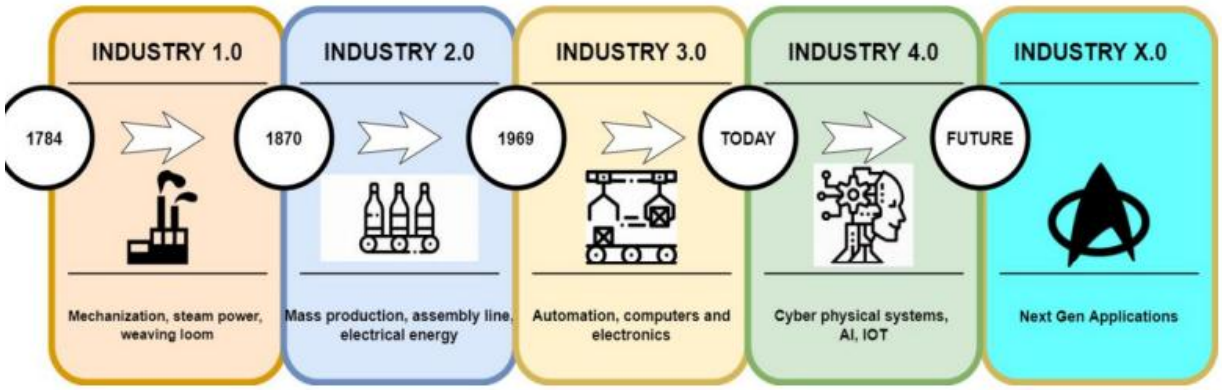

Fig. 1: Industry X.0 Revolution

PHM (Prognostic Health Management) is an underpinning discipline in several engineering and manufacturing sectors, where monitoring the enabling sophisticated technical infrastructure is essential. Better maintenance procedures, effective machine operation, and improved machine performance have always been PHM's key goals. The term "maintenance" describes a variety of technical, managerial, and administrative practices intended to ensure a system performs at its peak efficiency. Predictive maintenance, one of PHM's solutions, has gained popularity due to its ability to boost output while reducing maintenance expenses. The industrial sector has placed a high priority on timely maintenance in order to get optimal productivity at a cheap cost. Inadequate maintenance practices can reduce a piece of machinery's production capacity by 5 to 10 percent, according to a concerning evaluation. Manufacturers use a range of maintenance techniques based on their company's capabilities.

Need and motivation for Anomaly Detection under Predictive Maintenance

Anomaly identification or anomaly detection is the process of finding variables or outliers in a dataset that deviate from the expected trend and are frequently invisible to the naked eye (Abbas, 2024). These irregularities may be interpreted as warning indications of potential machine failure or as warning signs of operational flaws in machinery. What we might call 'anomalies' in this context are abnormalities that arise from the gradual deterioration of rolling machines or non-rotating equipment, like motors or gas engines (Keleko et al., 2022). This status should be viewed as an indication that the system needs maintenance and isn't operating at its peak efficiency, rather than as a total shutdown. Take roller bearings, for example, a popular type of rotating gear utilized in many manufacturing and industrial applications. An apparatus that positions rolling facets, like rolling balls, in between races is called a rolling-element bearing. The rotating components of these races rotate smoothly, with less abrasion and a tighter grip, thanks to their rolling or rotating action (Ucar et al., 2024). These devices are frequently employed in large-scale manufacturing and endure tough environments including high temperatures and high levels of wetness for prolonged periods of time. A number of factors, such as the following, can cause bearings to burst or develop characteristics. (i) Overloading results in poor bearing utilization; (ii) improper handling or installation of the bearings; (iii) improper lubricant, lubrication method, or waterproofing device; (iv) insufficient operating speed and

heating rate; or (v) contamination from foreign particles during the installation process. Figure 1 depicts the roller fault, the inner race (IR) fault, and the outer race (OR) fault. 6. The roller fault is one type of bearing issue. This calls for the development of a proactive system that can predict the remaining useable life of machinery, including bearings, and proactively detect abnormalities in them (Andrianandrianina Johanesa et al., 2024). Industry workers performing predictive maintenance on machinery will find this very helpful. Additional anomaly detection serves as a warning sign for the onset of a defect and as a signal for the complete shutdown of the machinery (Kliestik et al., 2023). Take a look at Figure 1.7, which shows bearing vibration over time and with prolonged use. Over time, when the bearing machinery is used, wear and tear will eventually cause abnormalities to appear. This would cause the machinery's vibrations to grow. A fault would then be started, resulting in even more intense vibrations. The bearing mechanism will eventually fail if remedial maintenance is not carried out after that. The remaining useful life of the machinery is the amount of time between the discovery of an anomaly and its eventual failure (Zsombok & Zsombok, 2023). For the machine supervisor, estimating the remaining useful life is a crucial prognostic technique. The goals of the study are as follows

1 To extract the different features of the machine monitoring sensor data and select the relevant features.
2 To design a deep learning framework for anomaly detection in machinery on benchmarked datasets.
3 To apply proposed deep learning technique for calculation of performance measuring parameters in smart manufacturing environment.
4 To analyze the performance of the proposed technique on real-world test data

Methodology

Figure 3.1 shows the proposed Anomaly-Onset Aware RUL Prediction system. One distinctive aspect of this framework is the development of a uniform method for defect diagnosis and prognosis. While supervised deep learning techniques are utilized to estimate RUL and establish anomaly initiation, unsupervised clustering algorithms are used for anomaly trend analysis. One of the most important factors in estimating the lifespan of any apparatus is vibration data. As the equipment gets closer to failure, the vibration signal's magnitude and distribution change. One vibration signal is equivalent to all of the data points in a specific time period. Furthermore, the signal's variance will be adjusted to account for its distribution. However, simple vibration data from sensors might not be sufficient to detect Pronostia bearing degradation. In order to convert raw machine data into more pertinent information that can be fed into the model, feature extraction is utilized. The selection of features that exhibit a strong connection with the target variables boosts the learning rate during model training, hence improving the predictive performance of the model. According to earlier research, time-domain and frequency-domain data can be very helpful in tracking the state of equipment from normal to failure. Accelerometer vibration sensors mounted on the machinery can be used to extract these features from the vibration data.

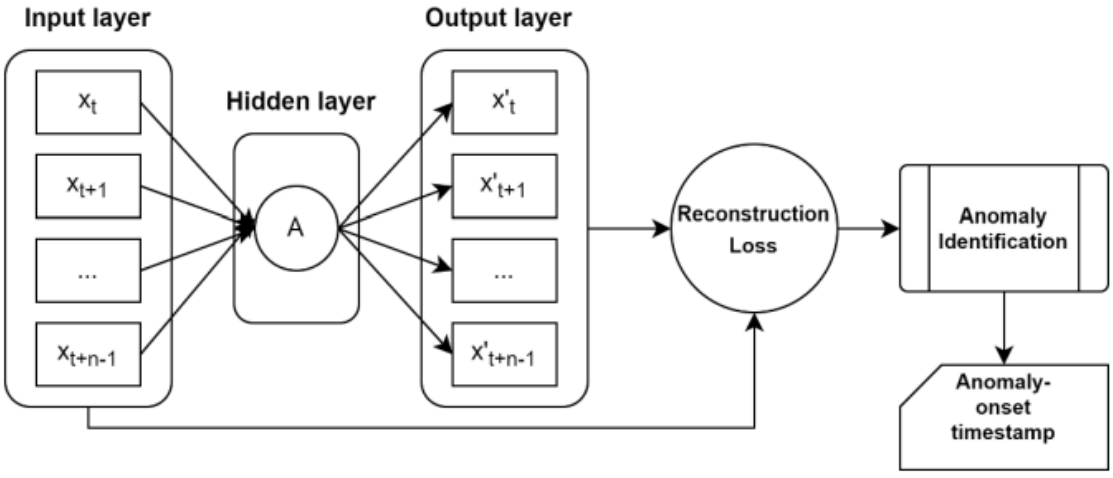

Fig. 2: Overview of Autoencoder Structure for Anomaly Timestamp Identification

To monitor the status of equipment, time domain features that show the trends related to the degradation of machinery from normal to failure are necessary. Time domain analysis helps identify and identify stereotypical or

transitory information in time series of incoming data. Equipment deterioration is reflected in the time-domain and frequency-domain characteristics. Overfitting may result from utilizing any of these characteristics at random as a model input. Overfitting occurs when a model performs well during training but significantly deteriorates during testing. Therefore, selecting the right qualities is essential. A technique for determining important equipment characteristics and removing those that have little bearing on the model's output or goal variables is feature selection.

Reducing the reconstruction error between the original space and the output vector is the primary goal of the autoencoder. To calculate the reconstruction error in this study, we used mean squared error, or MSE. To identify the abnormalities in the data, this reconstruction error is used as an anomaly score.

Performance Analysis

A clever feature selection technique significantly improves the model's performance and prediction accuracy. The following feature selection techniques were applied in this study. Each feature would be given a feature ranking or relevance using one of the following methods. A variety of methods for rating the input attributes in a predictive model and showing their relative usefulness in producing a forecast are collectively referred to as "feature importance". The majority of predictive maintenance datasets lack annotations or labels.

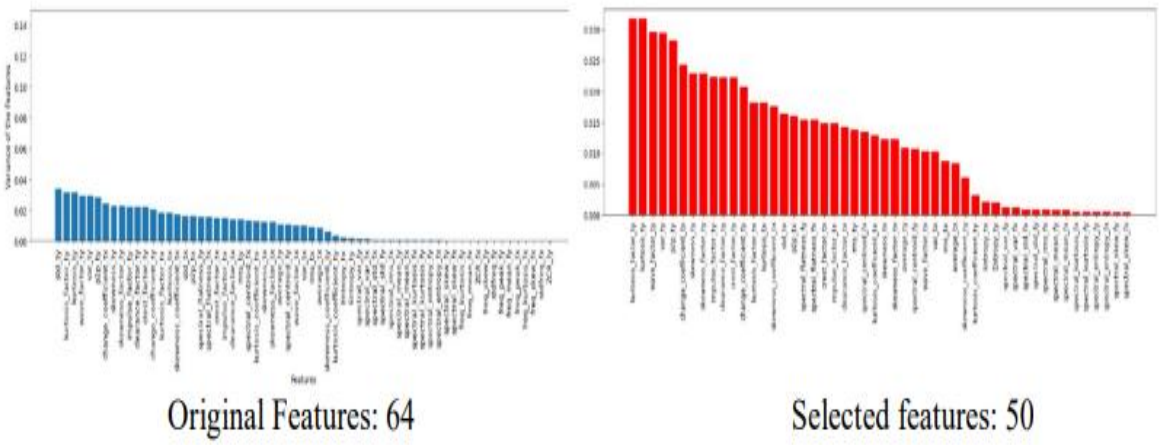

Fig. 3: Feature Ranking Before and After Application of Low Variance Filter

Over the course of the machinery's life, anomalies could have occurred at any time, leading to unusual vibrations. For anomaly pattern mining, unsupervised clustering is therefore crucial at this point. Using a distance-based metric, clustering separates data into numerous clusters and organizes representative samples. One of the different clustering techniques used in this investigation was K-means clustering. The K-means clustering technique was used to generate normal and anomalous groups. The ideal number of clusters can be determined using the Silhouette coefficient.

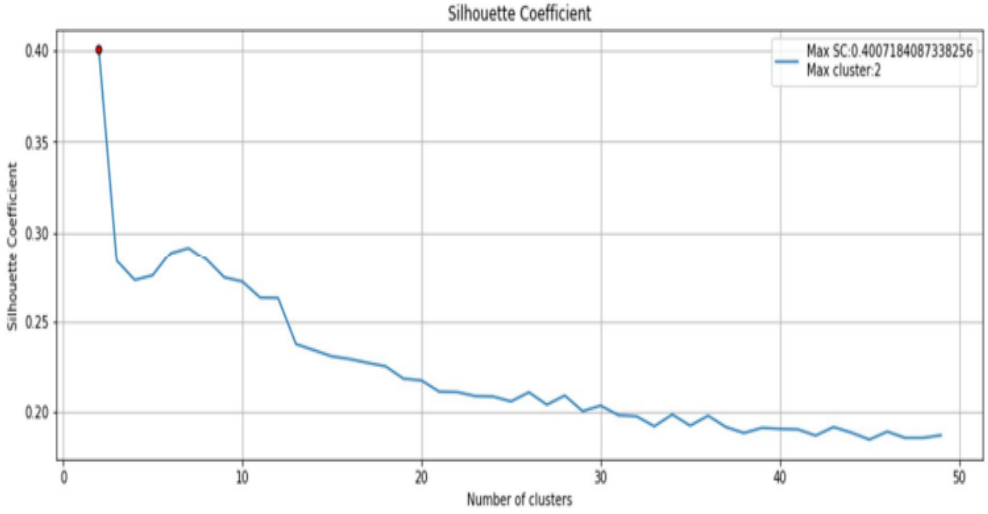

Fig. 4: Silhoutte Coefficient Indicating Two Optimum Number of Clusters for Tool Wear Dataset

The distinction between within-cluster compactness and isolation from the remainder is ascertained using the silhouette coefficient. One statistic that can be used to assess the effectiveness of a clustering strategy is the Silhouette Coefficient. Another common name for it is the Silhouette score. Its value ranges from -1 to 1. The silhouette coefficient implications are as follows: A value of +1 indicates that the clusters are clearly separated from one another, a value of 0 indicates that the clusters are unrelated or that there is little space between them, and a value of -1 indicates that the clusters were assigned improperly and need to be clustered again. In order to use supervised anomaly identification algorithms, one must be aware of the instance labels beforehand. The distribution of class labels is highly skewed toward the usual class, and outliers are rarely visible. In these circumstances, unsupervised or semi-supervised algorithms can help by treating data outliers as anomalies following pattern mining from partially-labelled data.

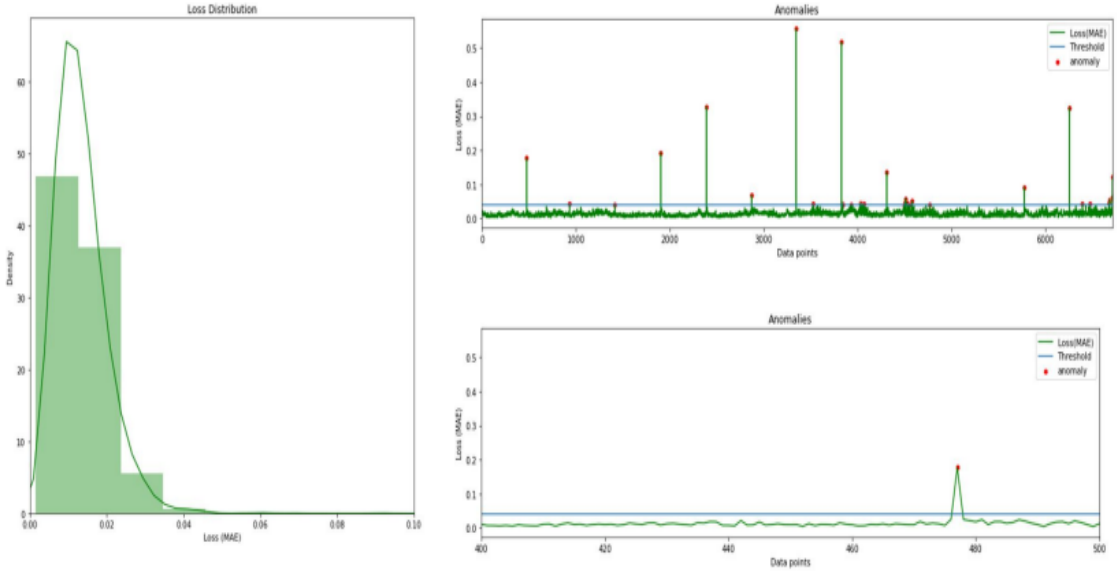

Fig. 5: Autoencoder-LSTM Reconstruction Loss Threshold for Tool Wear onset Detection Based on time + Frequency Domain Features

They use a threshold value based on the error difference between a known and unknown pattern to scale the occurrence of anomalies.

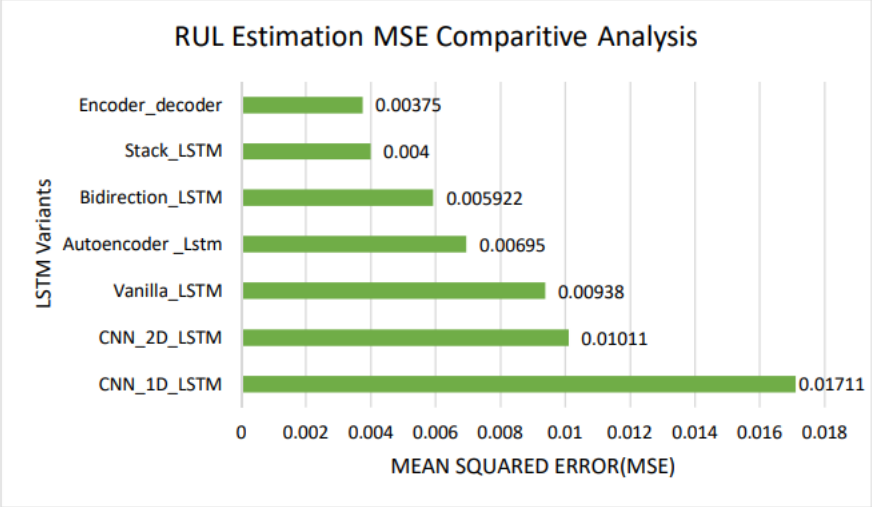

Fig. 6: Comparative Performance Analysis of LSTM Variants for RUL Estimation of Tool

Semi-supervised models called autoencoders use reconstruction loss to identify abnormalities. Because loss lacks labels, autoencoders are perfect for anomaly detection applications.

Conclusion

Determining the reference truth RUL for the collected data is one of the trickiest parts of building a deep learning model for RUL estimation. When the machine fails, RUL drops linearly. On the other hand, the RUL estimate is not well defined before deterioration starts. The majority of research determine a maximum RUL level and then presume continual RUL. Because different systems have different optimum values, determining the ideal RUL is arbitrary. Research on detecting abnormalities and predicting RUL as soon as the abnormality appears is few. RUL estimations during the wear-out stage have been the focus of most pertinent PHM research. The majority of processes do not address the identification of machinery degradation. Since it's challenging to determine the RUL while the equipment is in good condition, identifying wear early on is a helpful method for fault prediction. Most of these algorithms need a lot of data to understand previous examples in order to have robust RUL estimations.

References

Haque, R., Bajwa, A., Siddiqui, N. A., & Ahmed, I. (2024). Predictive Maintenance In Industrial Automation: A Systematic Review Of IOT Sensor Technologies And AI Algorithms. *American Journal of Interdisciplinary Studies, 5*(01), 01-30.

Abbas, A. (2024). AI for predictive maintenance in industrial systems. *International Journal of Advanced Engineering Technologies and Innovations, 1*(1), 31-51.

Ucar, A., Karakose, M., & Kırımça, N. (2024). Artificial intelligence for predictive maintenance applications: key components, trustworthiness, and future trends. *Applied Sciences, 14*(2), 898.

Kliestik, T., Nica, E., Durana, P., & Popescu, G. H. (2023). Artificial intelligence-based predictive maintenance, time-sensitive networking, and big data-driven algorithmic decision-making in the economics of Industrial Internet of Things. *Oeconomia Copernicana, 14*(4), 1097-1138.

Keleko, A. T., Kamsu-Foguem, B., Ngouna, R. H., & Tongne, A. (2022). Artificial intelligence and real-time predictive maintenance in industry 4.0: a bibliometric analysis. *AI and Ethics, 2*(4), 553-577.

Banerjee, D. K., Kumar, A., & Sharma, K. (2024). AI enhanced predictive maintenance for manufacturing system. *International Journal of Research and Review Techniques, 3*(1), 143-146.

Andrianandrianina Johanesa, T. V., Equeter, L., & Mahmoudi, S. A. (2024). Survey on AI applications for product quality control and predictive maintenance in industry 4.0. *Electronics, 13*(5), 976.

Zsombok, A., & Zsombok, I. (2023). Revolutionizing predictive maintenance: how AI-driven solutions enhance efficiency and reduce costs across industries. *Int. J. Sci. Res., 12,* 1168-1171.