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Design and Development of Data Driven Intelligent Predictive Maintenance for Predictive Maintenance

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Abstract--- Industrialists generally believe that maintenance is a necessary evil. A significant portion of all manufacturing systems' overall operating costs are related to maintenance. Industrial manufacturing businesses are severely impacted by the loss of production time and product quality brought on by an ineffective maintenance strategy. With the introduction of Industry 4.0, IoT-based data-driven automated remote-controlled operations and digitalised maintenance methods can be implemented by utilising cyber-physical systems methodologies. Maintenance scheduling and shop floor job allocation can be made simple using an IoT-based intelligent decision support system for machinery health management. One reliable way to maintain the health of machines and the quality of products is through predictive maintenance. Predictive maintenance uses machinery condition monitoring data, such as component vibrations, temperature, acoustic emissions, etc., to gain insights into the actual operating condition of the manufacturing system rather than depending on in-plant average life statistics or industrial field failure data. Real-time equipment status monitoring data collection and data acquisition from any location are made possible by developments in sensor technology and Internet of Things connectivity. Predictive maintenance of machine tools is becoming increasingly popular in the industrial sector as a way to increase production rates and improve tolerance of machined products. However, industrialists are discouraged from using predictive maintenance due to the high installation costs of the additional instruments and the complexity of computational tools. AI algorithms and other data-driven prognostics methods require little technical understanding of how machinery works and how failures occur. A promising AI computational approach for RUL estimation and machinery health prognostics is deep learning. However, there are numerous difficulties in putting deep learning algorithms for equipment health prognostics into practice.

Keywords--- IOT, Predictive Maintenance, Machine, Deep Learning.

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I. Introduction

Increased productivity and better product quality at the lowest possible production and maintenance costs are continual demands on manufacturing businesses. To keep up with the global competitiveness, manufacturing systems are now developed as extremely complex machine tools with powerful Computer Numerical Control (CNC) support. The operational state of the machine tool's functional parts and subsystems reveals the dependability of manufacturing systems. The lack of a suitable machine tool maintenance plan may become problematic as the industrial sector continues to embrace more digital technology (Aboshosha et al., 2023). The nature of the work done on machine tools and their constant operation cause wear and tear on their rotating and sliding parts, which gradually affects the machinery. Productivity and the quality of machined goods are negatively impacted by these mechanical defects to vital machine tool components (Wen et al., 2022). For machine tool systems to survive the industrial sector with 0% unexpected failure rates and little machinery downtime, an effective machinery health management approach is required. The technique of maintaining machinery in optimal operating condition to generate high-quality goods with optimal efficiency is known as machinery health management. In order to maximise asset availability, guarantee the quality of goods produced or services provided, and provide a safe working environment for their employees, machinery health management mainly entails maintaining industrial equipment (Fink, 2020). From basic reactive maintenance to preventive maintenance to condition-based maintenance (CBM), industrial maintenance has changed throughout time. An unexpected maintenance technique known as reactive or corrective maintenance involves letting the machine run until it breaks down and then fixing it. This maintenance strategy may cause unplanned equipment failures that significantly reduce output. A planned maintenance approach known as preventive maintenance involves scheduling time-based or periodic maintenance tasks ahead of time in order to avert failure. This maintenance strategy, however, results in repeated maintenance tasks and needless expenses. Time and resources that may be used for production are wasted on reactive and preventive maintenance techniques. The reactive and preventative maintenance approaches for the machinery performance index against service life are depicted in Figure 1. Reactive maintenance is only carried out when the machine deteriorates past the recommended service line and is unable to function as intended. After a catastrophic breakdown, the reactive maintenance plan also carries out rehabilitation tasks to return the machine to its original operating state. A periodic goal line, as used in preventive maintenance, is the point at which a machine undergoes routine maintenance procedures to return to its original operating state. This maintenance plan guarantees that the equipment will always run in the recommended service life state.

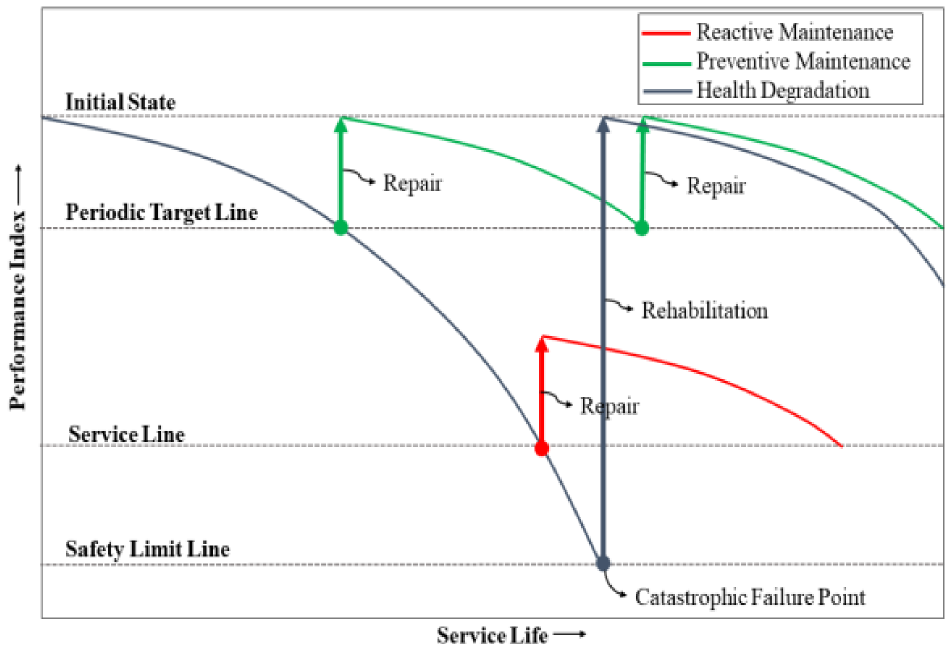

Figure 1: Illustration of Conventional Industrial Machinery Maintenance Strategies on Machinery Performance Index and Service Life

CBM is a maintenance method that monitors the actual state of an asset for choosing when what repair has to be done. The condition monitoring data gathered from running machinery serves as the foundation for CBM (Zhang et al., 2019). Predictive maintenance is a more sophisticated form of CBM in which future problems are anticipated well in advance of their actual occurrence through the use of data analysis tools and clever computer algorithms. As a result, the predictive maintenance strategy enables users to carefully schedule maintenance tasks so that the appropriate maintenance action is carried out at the appropriate time with the least amount of production loss and expense (Cheng et al., 2020). The extent to which predictive maintenance of manufacturing systems may be implemented helps to improve production quality, prices, and controls (Wang et al., 2023). Industry 4.0's predictive maintenance paradigm is supported by a number of technological enabling factors, such as a large number of sensors that can record any type of information sent by operating machinery (such as temperature, vibrations, or acoustic emissions), sophisticated computational resources for analysing the data collected, contemporary Internet of Things (IoT)-enabled remote connectivity methods, and big data cloud storage and computing technologies that offer real-time updates of machinery information for the prognostic analysis (Cinar et al., 2022).

In order to identify equipment failure trends and predict future failures, predictive maintenance typically makes use of both historical and current machine health deterioration data. The predictive maintenance approach tracks the functionality of the machine's functional components using condition monitoring tools. Any mechanical system uses time-series data, such as vibration signals, shock pulses, acoustic emissions, bearing temperatures, oil debris, oil pressure, and changes in electric current, to track the machine's operational state. This entails using various sensors, data collection devices, data processing methods, and calculation approaches (Serradilla et al., 2022). Because of the high expenses associated with sensor installation, data collection, and computing techniques, predictive maintenance is only performed on the most important machinery subsystems. Therefore, identifying the machine system's most important parts and the related failure modes is a prerequisite for using predictive maintenance. The choice of the best sensors for condition monitoring requires knowledge of the possible failure modes connected to the essential subsystems. To determine the possible failure modes of machinery functional components and the risk involved, failure modes and criticality analysis tools are used to analyse the information in the machinery log file that documents either a machine failure event, downtime, restoration, and related expenses.

II. Literature Review

The essential element of predictive maintenance is machine condition monitoring. Sensors are used to measure particular machine operating conditions in order to spot any anomalies that might interfere with the machine's regular operation. Both diagnostic and prognosis information, such as the defect, its location, its causes, and its anticipated failure time, are provided by the machine condition monitoring data. The condition monitoring data can also be utilised to assess the manufactured goods' quality, particularly its surface quality and dimensional tolerances. The most popular condition monitoring metric for mechanical systems is machine vibration monitoring. Vibration signals for machinery failure prognosis analysis are collected from the machine health degradation patterns. The basic method used by machinery health prognostics to estimate Remaining Useful Life (RUL) or Time-to-Failure (TTF) is to compare the machine's present operational condition with the past machine failure trend pattern. Techniques for health prognostics are divided into four categories: hybrid, physics-based, statistical model-based, and artificial intelligence (AI)-based (Zhang et al., 2019). For complicated equipment, the physics-based approach necessitates a deep understanding of the physics of failure mechanism, which is challenging to implement. AI and statistical model-based methods are data-driven strategies that use data on the health degradation of machinery to make predictions. While AI models make use of very few technical features of the system, statistical model-based approaches simply need empirical knowledge to build a relationship between the statistical model and failure mechanisms. AI techniques employ intelligent learning algorithms to identify patterns of machinery health decline, but their application was unpopular because of the learning process's opaque nature and the need for powerful computers. The data-driven methods train intelligent prediction models using information on machinery health degradation, which is then used to estimate the considered machine's RUL. For many years, the most widely used prognostic method has been based on statistical models. The most popular statistical models for machinery health prognostics include random coefficient models, autoregressive models, Wiener process models, Gamma process models, inverse Gaussian process models, Markov models, proportional hazards models, exponential deterioration models, etc. Given the improvements in computer power and their superiority in handling prognostic issues for intricate mechanical systems, artificial intelligence (AI) techniques have been gaining more and more attention. AI models for machine learning and deep learning are widely used in the diagnostic and prognostic study of machinery health. Artificial neural networks (ANN), neural fuzzy systems, support vector machines (SVM), support vector regression (SVR), k-nearest neighbour (KNN), Gaussian process regression (GPR), recurrent neural networks (RNN), long short-term memory (LSTM), deep belief networks (DBN), convolution neural networks (CNN), and others are the most well-known machine learning and deep learning architectures for failure prediction and RUL estimation. While technological developments support the use of AI algorithms for prognostics, choosing a network architecture and optimising hyperparameters are significant obstacles to their effective application. The accuracy of the RUL estimate models is directly impacted by the hyperparameter optimisation, which includes both structural and training parameters. To lower the computational complexity and increase prediction accuracy, hyperparameter optimisation uses computational search techniques such as grid search, random search, Bayesian search optimisation, etc.

The Industrial Internet of Things (IIoT), which creates an effective communication paradigm between the numerous industrial machines, systems, and users, is the industry's most alluring contribution to the most recent technological breakthroughs. For intelligent computational methods, IIoT makes use of cloud computing capabilities, cloud space, and cutting-edge sensor technologies that underpin the IoT. The predictive maintenance paradigm for industrial machinery can be enhanced by these technical developments. For the industrial sector, a maintenance decision support system that includes a failure warning system and a maintenance decision-making dashboard can be provided. Additionally, the system may control industrial processes and provide remote access to information about the health status of industrial machinery. Predictive maintenance is viewed as an asset to the overall industrial production management process, not a replacement for conventional maintenance techniques. The necessity of conventional reactive or preventive maintenance techniques cannot be completely eliminated. Given the high installation costs and the fact that only component problems that can be monitored using sensor technology might be taken into consideration, the user in any business should determine whether predictive maintenance is appropriate for the machinery.

III. Projected Method: Predictive Maintenance

The objective of this effort is to use intelligent data-driven computational methods for predictive maintenance and prognostic analysis of important machine tool systems. The purpose of the study is to look into the difficulties that the manufacturing sector faces while implementing a predictive maintenance strategy for its machine tool systems. In order to prioritise maintenance of essential components and identify potential failure modes, the study begins with a criticality analysis of a CNC lathe machine tool. Next, sensors are chosen, and a data gathering system is configured for the recording of machine health deterioration data. Additionally, data-driven methods are used to identify trends of machine health deterioration in order to develop intelligent prediction models. However, in the current era of Industry 4.0, there is room for disagreement on the significant hurdles associated with the implementation of intelligent data-driven techniques such as deep learning algorithms for machinery health prognostics. One significant drawback is the requirement for a sizable amount of machinery failure data in order to train deep learning algorithms. The implementation of intelligent health management of industrial machinery may be hindered by the difficulty and unpredictability of hyper-parameter optimisation, architectural design, and data training of deep learning algorithms. In order to encourage industrialists to start an autonomous equipment health management system, this research project attempts to reveal the black-box nature of deep learning algorithms and create an understandable prognostic platform with automatic hyper-parameter selection. Motivating industry practitioners to create an autonomous equipment health management system that includes intelligent prognostic model training algorithms and a machine health deterioration data gathering system is the main goal of this thesis. Such a solution fits into the current Industry 4.0 era by increasing the overall industrial value.

Proposed Model

On a separate testing dataset, the prediction accuracy of the developed predictive models is evaluated. For every predictive model, the RMSE between the actual and anticipated RUL is calculated. The response clip placed on the actual life pattern and the actual lathe spindle life deterioration pattern are both well-complemented by the projected RUL. For spindle lathe RUL estimation, it has been found that not all deeper LSTM and bi-LSTM network combination topologies provide more accuracy than single LSTM or bi-LSTM network structures. When it comes to lathe spindle RUL estimation, the LSTM plus bi-LSTM network design has the highest prediction accuracy (RMSE = 31.65), followed by the single LSTM architecture (RMSE = 40.01). When it comes to uncovering hidden patterns in time-series data, the LSTM architecture is highly effective. Accurate estimations can be obtained by further refining the learnt deterioration patterns using a bi-LSTM network. Additionally, it is noted that the training procedure and, consequently, the prediction accuracy are significantly impacted by the arrangement of the LSTM/bi-LSTM layer inside the layer architecture. It is found that deep learning architectures that start with a bi-LSTM network provide predictions that are relatively less accurate. This could be as a result of the bi-LSTM network learning time series data in both directions, which causes the evolving predictive model to overfit. The optimal individual hyperparameter choices for maximising prediction accuracy on lathe spindle data are determined by the Bayesian optimisation of LSTM/bi-LSTM and their combination architectures. For the lathe spindle unit's predictive analytics, the suggested Bayesian optimisation deep learning algorithm offers a platform for RUL estimation together with integrated hyperparameter self-optimization. Flow Diagram for Bayesian Optimization LSTM/bi-LSTM Network Algorithm shown in Figure 2.

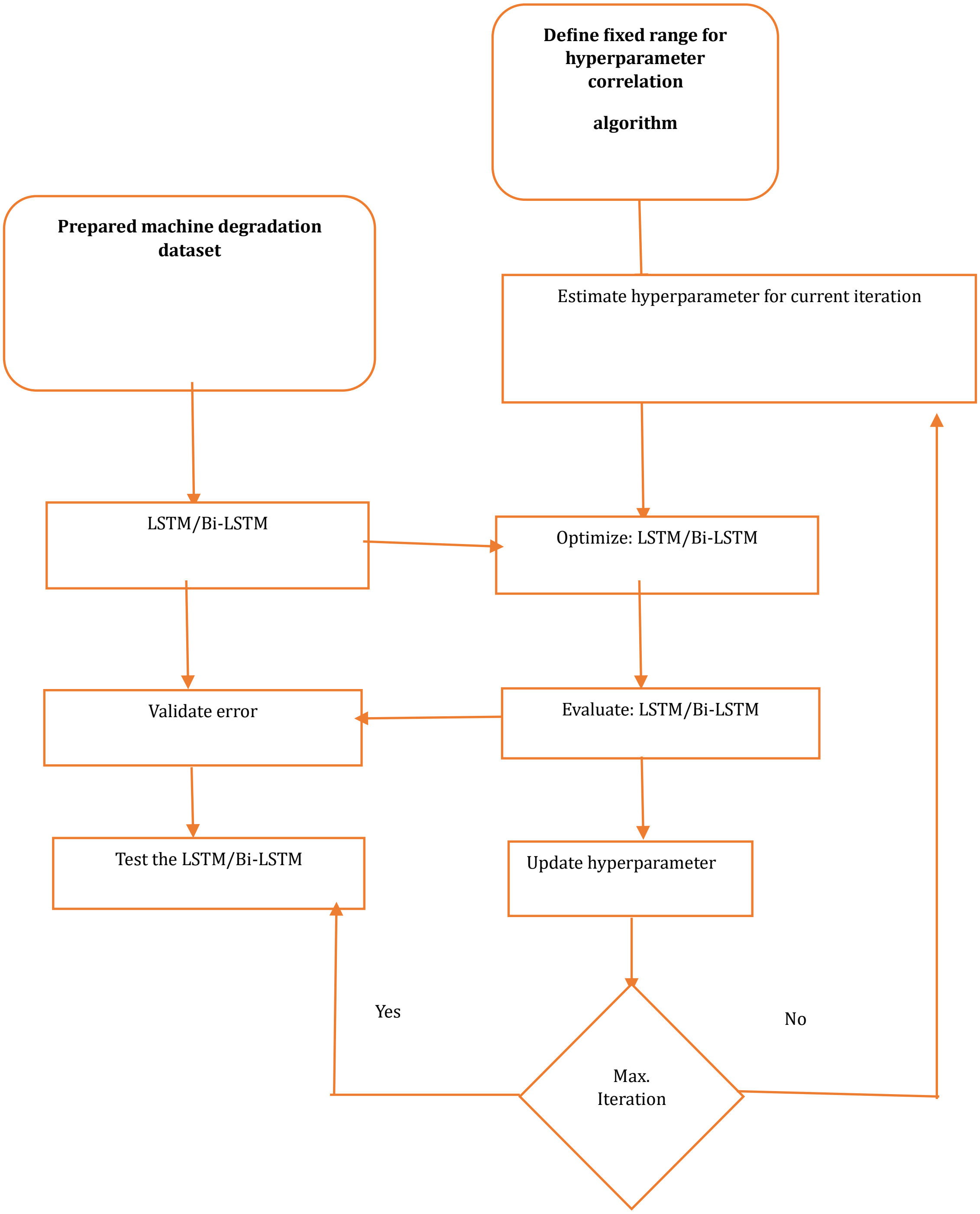

Figure 2: Flow Diagram for Bayesian Optimization LSTM/bi-LSTM Network Algorithm

IV. Results And Discussion

Figure 3 shows test observation graphs for LSTM/bi-LSTM network designs between real RUL and anticipated RUL along with the corresponding prediction accuracy (RMSE).

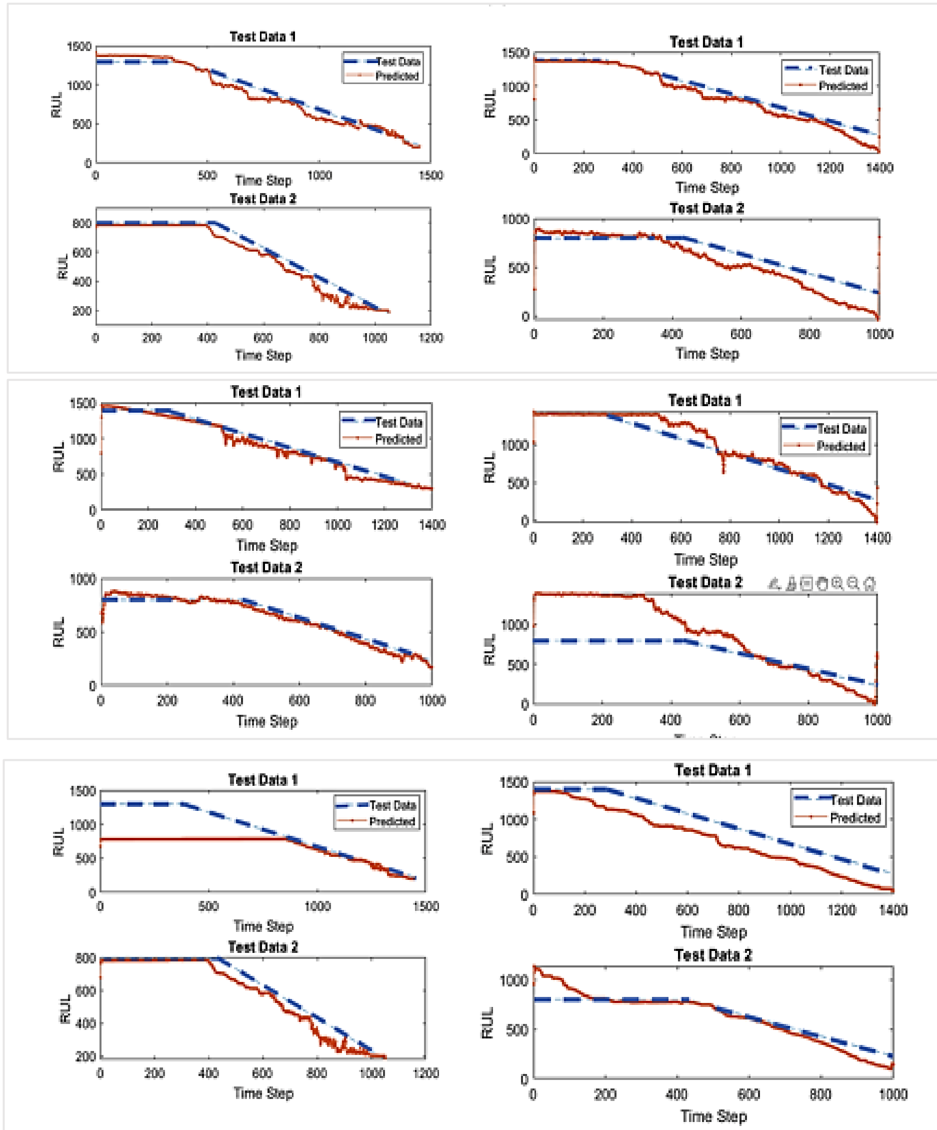

Figure 3: Actual RUL vs Predicted RUL

To adjust the SVM hyperparameters for a minimum estimated MSE between the predicted and actual RUL on the validation dataset, the method iterates frequently. After thirty iterations, the Bayesian optimisation method stops. An MSE plot, as seen in Figure 4, illustrates how Bayesian optimisation moves forward to determine a minimal observed MSE against an estimated minimum MSE for each iteration.

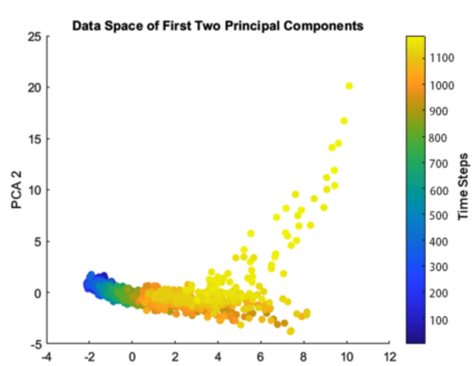

Figure 4: Data Space for the First Two Principal Components

To adjust the SVM hyperparameters for a minimum estimated MSE between the predicted and actual RUL on the validation dataset, the method iterates frequently. After thirty iterations, the Bayesian optimisation method stops. An MSE plot, as seen in Figure 4, illustrates how Bayesian optimisation moves forward to determine a minimal observed MSE against an estimated minimum MSE for each iteration. MSE Plot for Bayesian Optimization shown in Figure 5.

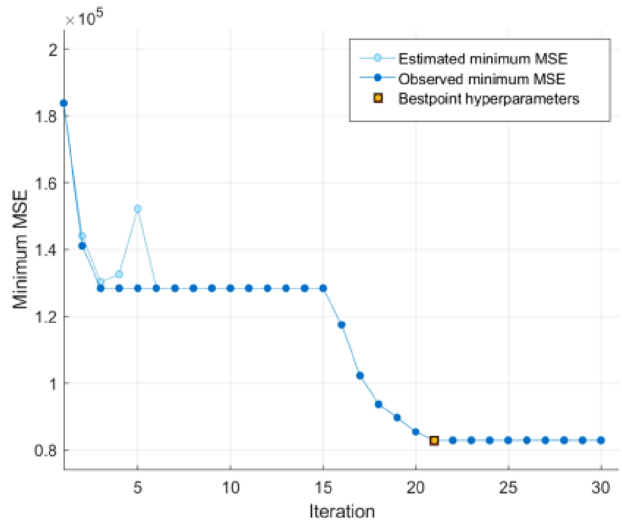

Figure 5: MSE Plot for Bayesian Optimization

Figure 6 displays the difference between the actual and anticipated RUL for the two test datasets. Response-clipping is applied to test datasets real RUL values until they equal 800. It is evident that the projected RUL makes an effort to follow the real RUL pattern from the first to the last time-step. For both test data 1 and test data 2, the pattern tracing is seen to get better as the time-steps approach the end. There is a satisfactory degree of concordance between the overall anticipated RUL and the actual RUL. For the supplied dataset, the Bayesian optimised SVM model yields a quantitative measure of prediction accuracy with an RMSE of 206.23.

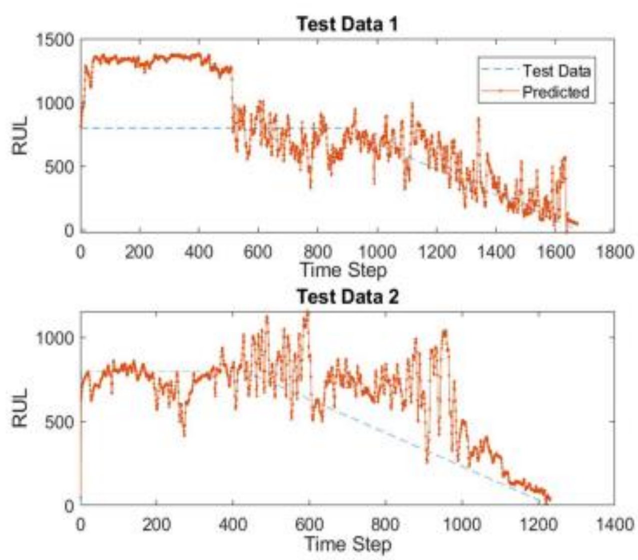

Figure 6: SVM Model the Variation of Actual RUL vs Predicted RUL

The prediction results obtained fairly follows the actual experimental test observations. The model prognostic regression analysis is an effective tool for RUL estimation from time-series machine degradation data. As well, the Bayesian optimization approach for the best hyperparameters setting is proved effective for machine learning algorithms.

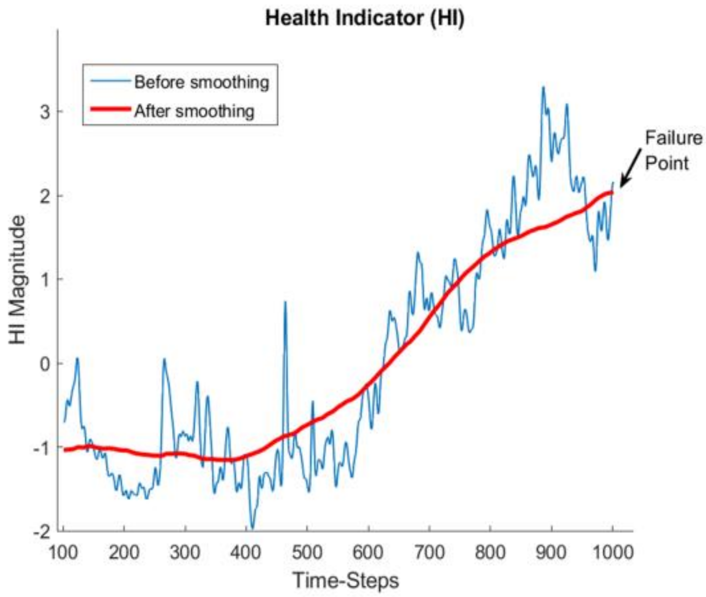

Figure 7: Constructed Health Indicator (HI)

The smoothed HI for bearing degradation is displayed in Figure 7. At the start of the component's life, the HI displays a consistent pattern, indicating that the component is in typical, healthy condition. A steadily rising trend of HI follows this step, signalling the emergence of mechanical unit flaws. A sharp rise in the trend signals that the component is getting close to failing and eventually failing. The exponential degradation model technique for RUL estimation is trained using this smoothed HI.

V. Conclusions

To estimate RUL using the best optimised hyperparameter sets, a Bayesian optimisation approach is applied to the lathe spindle dataset. For RUL estimate analysis, the lathe spindle health degradation model is also fitted with an exponential degradation statistical estimator model. When analysing time-series sequence data for prognostic regression, the LSTM/bi-LSTM deep networks have been found to be useful. The LSTM networks' long-term and short-term memory gradients are better able to reveal time-series data's hidden trend patterns. By employing the acquired vibration signature features to train a deep learning algorithm, the risk of underfitting the predictive models is eliminated. The data-driven prognostic models for RUL estimations are trained using the valuable machinery degradation information that is derived from the raw vibration signals. The requirement for larger data sets for intelligent learning model training has been superseded by feature extraction and feature selection techniques. Because the suggested approach totally eliminates the time-consuming process of manually adjusting the hyperparameters for training learning algorithms, Bayesian optimization-based self-tuning of hyperparameters largely dismantles the black-box nature deep learning algorithm.

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