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A Survey on Data-Driven Techniques of Remaining Useful Life Assessment for Predictive Maintenance of the System

Yashasvi A. Sarve[a], Anuradha C. Phadke[a,*]

[a]*Department of Electrical and Electronics Engineering, Dr. Vishwanath Karad MIT World Peace University, Pune, India.*

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* Corresponding author:

Anuradha C. Phadke
E-mail:
anuradha.phadke@mitwpu.edu.in

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A B S T R A C T

To maintain the system in its ideal state, maintenance is essential. In contemporary technological systems, predictive maintenance is a maintenance method that is given more consideration when planning maintenance strategies. Predictive maintenance helps enhance safety, increase asset life, minimize downtime, avoid over-maintenance, lower maintenance costs, and help in the continuous assessment of a system. The fundamental objective of predictive maintenance is to acquire accurate information on when to schedule maintenance based on the system's actual health before it breaks down completely. Remaining useful life (RUL) prediction is in high demand in modern industry because it serves as a foundation for predictive maintenance scheduling. Proper Estimation of RUL is the most important step in predictive maintenance. Under the same or close prediction error, an underestimated RUL is preferable to an overestimated one because an overestimated RUL increases the risk of unexpected shutdowns, which can have disastrous consequences. As a result, it is necessary and significant to properly estimate the RUL, which reduces the possibility of incorrect maintenance scheduling decisions. Several novel methodologies for RUL predictions have been developed based on the distinct scenarios depending on the system. This study highlights a variety of recent research trends toward precise RUL estimation.

1. INTRODUCTION

Manufacturing systems must maintain high productivity and low production reparations to survive in a highly competitive business environment. Good engineering standards, efficient operations and necessary maintenance are required to keep a modern multi-technological system functioning optimally. However, unplanned, arbitrary machine failures can have a big impact on how well the production system runs. Systems are compelled to stay in a transient phase, which exposes them to longer lasting and more frequent unplanned machine failures, leading to low productivity and low-quality rates [1].

Reduced machine breakage, increased production, and continued product functionality are all directly correlated with maintenance [2]. Maintenance planning is divided into three categories, depending on when the maintenance action is triggered. The first is corrective maintenance, in which once the component fails, maintenance action is triggered. The second is preventive maintenance, which depends on the time interval set by the manufacturer and is planned, for example, kilometers, cycles, days, etc. The third is predictive maintenance, which aims to determine the accurate time to trigger maintenance based on the remaining useful life of the system.

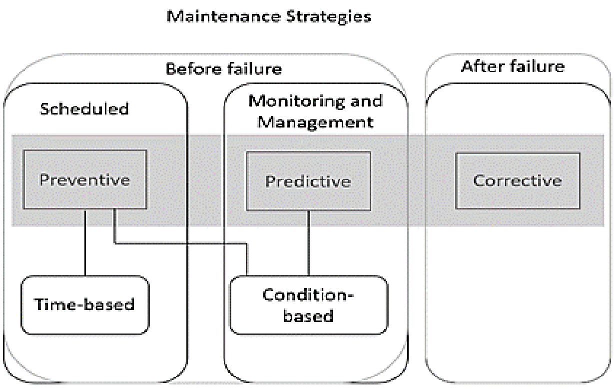

Fig. 1. An overview of Maintenance strategies.

Due to their high proficiency and low cost, predictive maintenance has been acknowledged as one of the most promising support approaches for manufacturing frameworks. According to the health of the machine, maintenance is planned. This lessens unplanned equipment breakdowns and unneeded maintenance occurrences. The goal of predictive maintenance is to provide a more accurate prediction of when maintenance intervention is required by organizing maintenance tasks in accordance with the system's real health status. Due to its potential advantages in terms of reliability, security, and maintenance costs, among many other advantages, predictive maintenance research is getting significant industrial and academic attention. Due to its potential advantages in terms of dependability, security, and maintenance costs, among many other advantages, predictive maintenance research is receiving significant business and scholarly scrutiny. Predictive maintenance, as explained by [3], can reduce maintenance expenses by 25%–35%, eliminate crashes from 70%–75%, reduce downtime by 35%–45%, and increase production by 25%– 35%.

Predictive maintenance is frequently performed utilizing specialized computer frameworks that coordinate one of the models to perform symptomatic and prognostic assignments. As the complexity of innovative frameworks increments over time, basic modeling approaches don't fulfill all capacities and goals of the predictive maintenance framework. The estimate of remaining usable life (see Fig 2), which is an estimate of the number of cycles that a framework is anticipated to be able to perform in understanding of its intended purpose before guaranteeing time, could be a pivotal issue in predictive maintenance, it is considered the center specialized viewpoint in predictive maintenance.

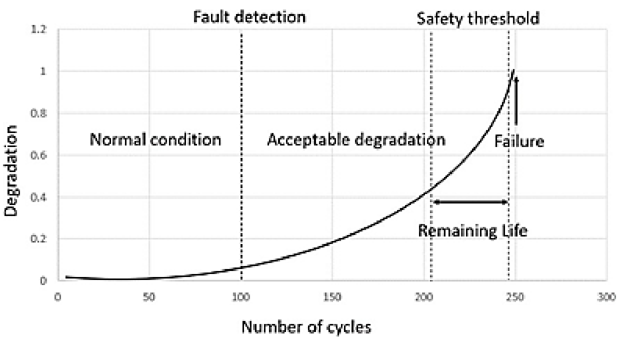

Fig. 2. Graph of RUL Estimation.

Owing to the uncertainties involved in the prediction process, there are uncertainties in RUL predictions; identifying these uncertainties and being able to quantify them is important. These uncertainties can be attributed to data, changing health conditions, environmental loads, and the model used for prediction. Depending on the condition indicator, a minimum threshold of functionality is set; if the threshold is surpassed, the system is considered to break down. Although this basic criterion seems to be easy, it is challenging owing to the degrading dataset, which is constantly changing due to environmental and process degradation. This changes the standard and regulatory requirements that lead to the development of new technology for tracking these degradation processes, depending upon the degradation process.

The present survey focuses on: the important role of maintenance in production, the key items relating to machine maintenance and techniques for predicting the RUL of a system.

2. SURVEY DETAIL

The study of RUL predicts when the system will fail provided the present state. A system fails when it no longer provides the desired output. For example, a battery fails when it is required to charge frequently while traveling a small distance. The goal is to predict beforehand when system will fail. Many techniques have been developed to predict RUL. These techniques can broadly be divided into two categories: model based methods and data-driven methods.
In model-based methods, mathematical formulae are developed for the system under consideration, and then using the model RUL is predicted. This approach is used in many cases, but it is extremely difficult to formulate a mathematical model for complex systems where the underlying physics are complex; therefore, more assumptions are made. Whether the assumptions are correct or not needs to be cross-checked with real data collected from the system, which requires extensive domain knowledge. In contrast, data-driven methods, data is collected in huge amounts from the sensors available, and analyzing this data idea of machine condition is determined, which will help to predict the RUL. In this method, no assumptions are made regarding the system; this method improves and provides reliable predictions. This paper gives an audit of the data-driven strategies utilized for RUL estimation (Fig. 3.).

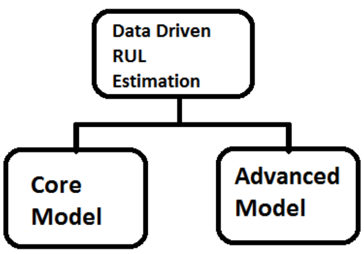

Fig. 3. Data-driven RUL estimation techniques.

RUL estimation techniques under the Advance model group can be further classified into three subgroups namely, neural network models, probabilistic models, and hybrid models, as shown in Figure 4.

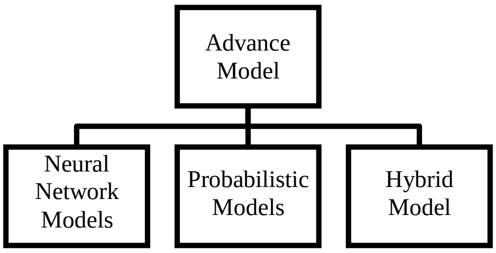

Fig. 4. Various Advanced models.

2.1 Core Model

A core model refers to a foundational and relatively simple algorithm or model used as a starting point for solving specific tasks or problems. Core models are typically straightforward, easy to understand, and serve as a baseline for performance evaluation. They are often employed at the initial stages of model development to establish a basic level of performance before exploring more complex techniques. As depicted in Fig. 5, core models can include linear regression, logistic regression, k-nearest neighbours, or decision trees. These models are characterized by their simplicity and interpretability, making them useful for tasks where transparency and ease of implementation are important. One of the primary purposes of core models is to provide a benchmark against which more advanced algorithms can be compared. Data scientists and machine learning practitioners often begin with core models to gain insights into the problem's characteristics and to assess whether more sophisticated techniques are necessary for improved accuracy and generalization.

Depending on the available data, the machine learning core model that should be used is discussed. Within the paper [4] Mihaela Mitici et.al addresses the challenge of foreseeing the RUL of lithium-ion batteries utilized in electric vertical take-off and landing airplane. This consideration proposes a data-driven machine learning approach to prognostics that employments a combination of feature engineering and supervised learning calculations to expect the RUL of batteries. The essential step inside the proposed approach is to perform feature engineering to remove significant features from battery data. These highlights incorporate electrical, warm, and mechanical parameters that are known to impact the execution of lithium-ion batteries. The feature engineering process is utilized to convert crude battery information into a set of features that can be utilized as inputs for machine learning models. The second step in this approach is to train supervised learning algorithms using the extracted features and historical battery data to predict the RUL of the batteries. The models used to obtain useful results are Random Forest regression (RFR), Gaussian process regression (GPR), Support Vector Machine (SVM), Extreme Gradient Boosting (XGBoost), and multilayer perceptron.

In case the connection between the input and yield is non-linear, which is the case when considering the discharge of the battery; a SVM is utilized, which could be a supervised machine learning strategy. RF regression works based on the decision tree. Points arbitrarily chosen from the preparing dataset were utilized to construct forest trees. The mean is utilized to improve the precision, and the overfitting issue is additionally considered. GPR is based on the kernel method, which is a non-parametric probabilistic method that considers prior knowledge and obtains a posterior hypothesis to determine the output. Because of the advantage of adapting the hyper-parameter adaption, using GPR, one can obtain the same results as the SVM and neural network. The XGBoost model works on the concept of a gradient-boosted decision tree, which uses a parallel tree to achieve more accurate speed and performance. An MLP may be a neural arrangement that has numerous hidden layers to move forward its steadiness. The third step in this approach is to validate the trained machine learning models using real-world battery data collected from an eVTOL aircraft. The parameters that are taken into account to evaluate the performance of the models are the mean absolute error, the root mean square error and the mean absolute error in percentage. Using all the above- mentioned machine learning models, SOH and RUL are calculated for each machine learning model and evaluated based on performance metrics. When using RF regression, The lowest mean absolute error of 1.33% and the lowest mean absolute error of 54.33 was obtained by using RF regression compared with other models. The study also highlights the importance of feature engineering to improve the accuracy of predictions.

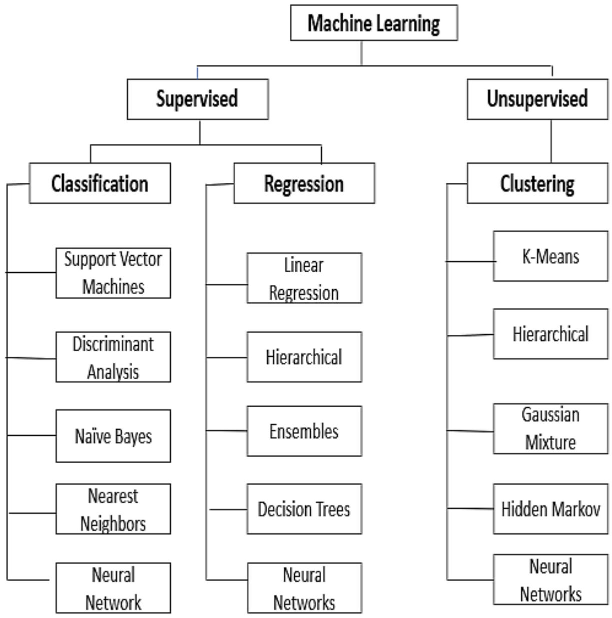

Fig. 5. List of various ML Models.

If there is any abnormality in the dataset, then how to tackle the problem using SVM is discussed in this paper. In this study, Xiong et al., [5] suggested a support vector machine (SVM) method for the RUL calculation. The SVM has a high generalization capability. SVMs are based on certain conditions to yield a more accurate outcome. Despite this advantage, an accurate output is lacking when an abnormality is present in the training dataset. SVMs are sparse in nature and use a limited amount of data; therefore, any error in the training dataset will lead to a significant effect when predicting results. SVMs are typically used to solve classification problems. The classification was based on hyperplane construction. The optimal hyperplane was constructed using the structural risk-minimization criterion. Based on the regions created on the sample dataset, SVM categorizes the unknown data sample accordingly. SVM regression is a supervised learning problem, the classification and regression are based on finding the best fit line. The best-fit line for the regression is the hyperplane, which consists of most points. Sparsity is considered an advantage of the SVM model, which makes the calculation easy. However, if any outlier data point is present, it leads to a shift in the hyperplane and does not yield better results. To solve this problem and improve the performance of SVM, a method based on Weighted Least Squares Support Vector Machine (WLS-SVM) was developed. They proposed a method that combines mean squared error with weighting functions to improve accuracy. This concept is used to predict the lithium-ion battery lifetime. The proposed method extracts health indices (HI) from discharge-power curves. Based on the correlation of HI with the duration of use, the remaining useful life was predicted. The results of WLS-SVM are compared with other machine learning algorithms, such as Back propagation Algorithm in Neural Networks (BPNN), SVM and GPR. The root mean square error for WLS-SVM was 8.83% compared to 41.80% for BPNN, 14.33% for SVM, and 22.54% for GPR, which is notably higher than that obtained in WLS-SVM. This study infers that, with a limited dataset, RUL can be calculated more efficiently with WLS-SVM. The early life prediction of lithium-ion battery degradation is predicted with high accuracy using the same method.

A new approach to predicting the life of lithium-ion batteries using piecewise linear models is presented in [6]. Piecewise linear model with automatic feature selection for end-of-life prognosis of Li-ion batteries is used. Predicting the end-of-life of these batteries is crucial for ensuring their safe and efficient operation, as well as for maximizing their lifespan. The piecewise linear model is based on the concept that the dataset is divided based on a constrained range in small linear models without compromising the overall performance of the battery or other components. The challenge is to decide based on which parameter the dataset can be divided; it can be based on the voltage or state of charge or region, or how a cell degrades at different rates or time spitting bases. In this study, a new method is designed in which the most correlated feature is found first; here it is found using Pearson correlation. This feature acts as a one-stop for the partial linear model. Then, a monotone function is created based on the highest priority feature using the concept of a weighted moving average. Using the second derivative, the point with maximum curvature is calculated, and in between, the models are fit. The new approach was validated using Gaussian process regression (GPR), and the new model performed better at the 95th percentile. Using the new approach, the features reduce the size of the dataset, which provides an additional benefit. In general, this paper presents an important commitment to the field of battery forecast by proposing a modern strategy for foreseeing the end-of-life of lithium-ion batteries utilizing piecewise-linear models and mechanized feature determination. The proposed strategy has the potential to improve the security and effectiveness of lithium-ion batteries in different applications, as well as illuminate choices related to battery substitution and upkeep.

2.2 Advanced Models

Advanced models in machine learning represent complex and sophisticated algorithms designed to handle intricate and challenging tasks. These models are characterized by their ability to capture intricate patterns, relationships, and nuances in data, making them suitable for tasks that involve high-dimensional data or intricate data structures. Examples of advanced models include deep neural networks, convolutional neural networks (CNNs), recurrent neural networks (RNNs), gradient boosting machines, and transformer models. Advanced models often require substantial computational resources and extensive datasets for training. They are selected based on the complexity and specific requirements of the problem at hand. While they offer the potential for superior performance, they also demand careful hyperparameter tuning, data preprocessing, and expertise in model design. The advanced RUL estimation techniques are grouped into 3 sub- groups namely Neural Network Models, Hybrid Models, and Probabilistic Models.

2.2.1 Neural Network Models

The neural network Models (see Figure 6) can process sequence data and predict outcomes based on both the most recent and earlier inputs. NNs are excellent for time- series data, including sensor measurements that can be used to forecast a system's RUL. NNs may be trained on both labeled and unlabeled data and can capture temporal dependencies in the data. Network based approaches like LSTM, DGN, and CNN for the prediction of RUL are discussed.

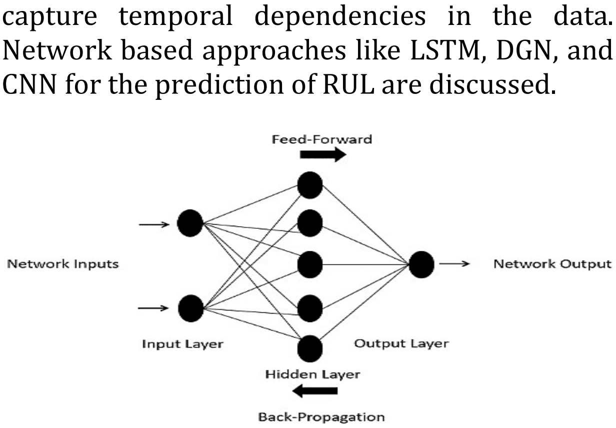

Fig. 6. Neural Network Model.

An LSTM-TL-WP method for RUL forecast using real-time deterioration information was proposed by Xiaowu Chen et al. [7]. This work suggests a new method for adaptively tracking the degradation trend in data in an effort to address the shortcomings of the current Weiner procedure. Stochastic processes are used when there is uncertainty or randomness in data points. To describe the degradation of the system, stochastic processes will be determined more accurately compared to other Machine Learning algorithms. Therefore, these methods are appropriate for calculating the RUL of a system. Wiener process WP is most commonly used because it is more efficient than other processes, however it also has its disadvantages, for example one system considered at a time it will have a pattern of distribution trends different, so it is very difficult to find the most suitable attenuation function for WP. Since WP relies on Markovian hypothesis, which does not take historical consideration states into account and has a larger number of parameters, it is challenging to discover the best solution and the anticipated RUL will be off. In this study, a new method is discussed to determine the decomposition trend in the current Weiner process. The new method is based on LSTM. First, the degradation trend is adaptively tracked, and the long term memory in LSTM solves problem of the Markovian assumption. The proposed method uses a smaller number of parameters for the solution, which makes it easier and more optimal, and then uses the concept of transfer learning. Transfer learning is helpful in updating the value in real time so that real-time predictions can be calculated. This method was named LSTM-TL-WP. The LSTM-TL-WP model is assessed on two simulated datasets and the dataset from Maryland University's Center for Advanced Life Cycle Engineering. In terms of correctly forecasting RUL, the LSTM-TL-WP fared better.

Modeling a time- varying trajectory using a dynamic governance network to predict the remaining useful life is presented in [8]. A new approach to predicting the RUL of a machine by means of modeling trajectories' change over time based on a dynamic governance network (DGN) is implemented. The currently available studies do not consider the physical dynamics behind RUL prediction and predict the fluctuating RUL, which contrasts with what is needed. To solve this problem, RUL prediction is considered as a time-varying trajectory modeling problem that is analyzed by taking the difference between a smooth RUL curve and a random attenuation and proposes DGN to find the RUL curve from the lifetime observations of the series. The ordinary differential equation (ODE) parameterized by a neural network is used to describe the equation of the RUL curve. To limit the space of the curve, a non-negative function is added each time during the forward propagation of the ODE. A super network with time-invariant parameters and time-varying network architecture is used to determine the time-varying factor in DGN, which is dynamically, determined using deep reinforcement learning algorithms. The formed time-varying curve provides insight into the RUL prediction. The model is evaluated using two datasets, that is, the N-CMAPSS dataset, which provides the run-to-fail data of the fleet engine, and the XJTU-SY dataset, which is another dataset that consists of a rolling bearing dataset and contains the run-to-failure horizontal and vertical vibration data. The result shows a state-of-the- art approach in which the DGN not only predicts the smooth RUL curve, but also captures the universal dynamics of the dataset. In summary, the proposed method provides an efficient and accurate method for predicting the RUL of a machine using a time-varying trajectory modeling approach based on DGN. This could be important in different mechanical settings, where exact RUL forecasts can help decrease downtime, increment effectiveness, and lower support costs.

Various factors affecting the RUL estimation are discussed in the paper [9], and it proposed an effective method which is the amalgamation of imperfect RUL prognostics into maintenance planning. Predictive maintenance scheduling is an important aspect of aircraft engine maintenance, as it helps ensure the safe and efficient operation of engines while minimizing maintenance costs. Traditional methods for predictive maintenance scheduling often rely on RUL prognostics that assume perfect knowledge of the RUL. However, uncertainty is always associated with RUL prediction owing to various factors, such as operational conditions, environmental factors, and manufacturing defects. These factors lead to errors in evaluation metrics such as RMSE, false negatives, MAE, and false positives, which are sometimes not considered. To solve this problem, an alarm-based system is proposed in this paper, based on safety limits periodically updating the measurements as they become available. When an alarm is triggered, it indicates the scheduling of the component maintenance task. The triggering time of the alarm is crucial; if the triggering time is late, then the component will fail and there will not be enough time and resources for maintenance. If the triggering alarm is early, it may result in re-scheduling the maintenance several times. A genetic algorithm was utilized to optimize the arrangement of activating a caution based on the security margin. The proposed system was applied to a fleet of 20 airplane, which comprised of two turbofan motors. RUL prognostic is performed using a CNN, and the values are updated regularly. Using this framework, the alarm is triggered early enough, which helps in scheduling an additional task to prevent failures.

Finding correlations between features in complex systems can be challenging; Z. Meng and colleagues examine several solutions to this problem. [10] explored RUL prediction of rotating equipment while considering the connection between local and global temporal properties in carrier vibration signals. It is challenging to explain the correlations between features because of the complexity of these conventional vibration prediction algorithms. The Transient Attention Matching (TAF) mechanism, an assignable optimization structure for intermediate features, is used in this paper's proposal of a new convolutional network to address this issue. The channel feature is related to temporary self-attention via the remaining connection. and a competitive merging is added to redistribute the weights of the features. It has two sub-modules: competitive temporal fusion and separate temporal self-attention (STSA). Its two sub-modules, competitive temporal fusion of attention (CTAF) and separate temporal self-attention (STSA), were utilized to obtain correlations between the temporal positions of multi-sensory input and to better represent local temporal aspects. At several levels, CTAF is utilized to improve the extraction and merging of global temporal information. The suggested model is TAFCN since it combines all these submodules to create the TAF, which is then integrated with a convolution network to combine local and global information. A roll dataset was used to test this model, and the results revealed that the TAF module can capture significant signal and noise interference and that RUL has higher prediction accuracy than other models current model.

In the work by Sarve and Phadke [24], various machine learning and deep learning models were implemented to estimate Remaining Useful life of fan nozzle of IP (Ingress Protection) testing machine. The machine learning models implemented are Linear Regression, Random Forest, XG Boost, Decision Tree, and Gradient Boosting and the deep learning models implemented are Long Short-Term Memory (LSTM) model and Gated Recurrent Units (GRU) model. In the presence of noisy data, the adaptive learning strategy of XGBoost has demonstrated best performance amongst the implemented ML models and GRU (Gated Recurrent Unit) models outperformed amongst the implemented Deep Learning approaches.

2.2.2 Probabilistic Models

The probability distribution of the RUL of a machine or system is estimated using a probabilistic model for RUL estimation. Probabilistic models provide a more complex understanding of the uncertainty surrounding RUL predictions than deterministic models that only give a single point evaluation of the RUL. When the estimate is critical to decision making and it is necessary to quantify the uncertainty of the estimate, probabilistic models can be useful. There are various probabilistic model types for RUL estimation, including Bayesian models, Gaussian processes, and Hidden Markov models. This section discusses the various probabilistic models used for the RUL estimation. The basic block diagram is explained in Figure 7.

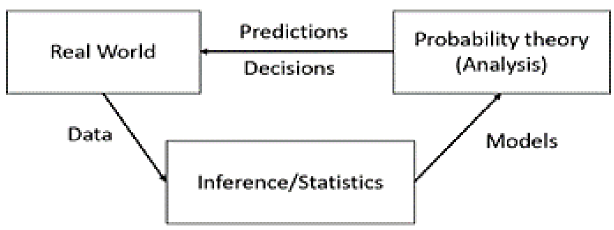

Fig. 7. Basic block diagram of Probabilistic Model.

Data uncertainty about the Bayesian model approach was discussed by Milazzo et al. [11], who proposed a probabilistic model to predict the residual life (RUL) of atmospheric storage tanks used in the oil and gas industry. The proposed model uses a Bayesian approach that incorporates uncertainties in the input variables, such as the corrosion rate, wall thickness, and tank geometry. The model also takes into account the impact of inspection and maintenance actions on the RUL estimate. To validate the proposed method, we conducted a case study using data from a refinery storage tank. The statistics behind finding the pitting corrosion were based on extrapolating the small patch of data to the entire dataset. The Small patches can follow the distribution of the entire data sample. The results show that the recommended model provides more accurate RUL predictions than traditional deterministic methods. The authors also demonstrate the sensitivity of the model to various input parameters and the importance of regular inspections and maintenance actions to extend the RUL of the reservoir.

Degradation angle is a new concept used to improve the process of capturing the decline trend of data [12]. Wiener processes are used to describe the degradation process in a two-step prediction model; however, when using a single drift function, one cannot accurately track the degradation of the two steps. These attenuations also occur over a long range, and it is difficult to get the point of change in the attenuation steps, which ultimately reduces the prediction accuracy of the model. A novel approach that uses deterioration angle (DA) to address the issue has been developed to address it. Both the slow degradation model (SDA) and the accelerated decline model (ADS) are referred to as DAs; the former determines the point of change during the slow phase of decline, while the latter does so during the latter. According to the DA definition and time to first attack, the PDF functions of SDS and ADS are calculated to estimate degradation; accordingly, the Bayesian model is updated. DA is based on the concept that the degradation rate of a component is different; so, the generated radians are different, converted to an angle and the DA concept comes into play. The findings of the suggested method are compared using the power law degradation model (PLDM), the exponential low degradation model (ELDM), and the model after being tested using a rolling dataset anticipate two phases. The proposed model has higher prediction accuracy than other models.

This paper [13] discusses the RUL calculation based on the exponential deterioration model of nuclear power machinery after the alarm sounds from the failure warning system. Exponential decay models do not require more data to predict; therefore, RUL can be predicted based on historical data rather than data from device operation until failure. Once the data are processed, important features are extracted and selected, dimensionality reduction is performed on multiple degradation variables using the Bayesian process, and an exponential degradation model is constructed. A condition parameter was created for each of these several variables, a systematic error threshold value was established, and the RUL was calculated using linear regression. Additionally, a mapping between the RUL and the degradation trend was discovered. The electric turbine that was a part of the actual nuclear power monitoring data was used to analyze this model, and the findings supported its efficacy.

The RUL was estimated based on a set of circumstances, but it will be applied under actual circumstances [14]. Despite the existence of numerous prognostic models, RUL prediction still has some flaws. More crucially, none of the disclosed efforts attempt to label their RUL value before domain adjustment and instead treat suspension history in the target domain with unlabeled data. The reported transfer learning methods can only forecast the RUL of the device under comparable operating conditions because suspend history is not taken into consideration during supervised learning; they cannot, however, resolve the prognostic issue in specific working circumstances. In order to address this issue, a transition- forward learning model for inter-domain prognostics is developed in this study using the source domain's error history and the restricted pause history. In order to address this issue, a transition-forward learning model for inter- domain prognostics is developed using the restricted pause history of the target domain and the error history of the source domain. The suggested model uses this index to estimate the time to error (FOT) and time to error (FT) of the two-domain training dataset. It is based on self-organizing consensus models (COSMO). The health status can be used to categorize all training histories. The prognostic domain was utilized to calculate the distance between the conditional and boundary probability distributions in the two domains based on the maximum mean deviation (MMD). A trace collector standardization technique has also been designed to help domain functionality degrade in a clear and continuous manner. Labeled data are needed to optimize model parameters, but they are not readily available in the target domain for cross-validation. Therefore, a heuristic with a parallel framework is provided for model training and RUL prediction. This will aid in explicitly validating the model's uncertainty and input parameters. These two datasets—the C-MAPSS dataset and XJTU-SY—were utilized for bearings in order to assess the suggested technique. Using this model, RUL accuracy was increased by 30%.

The RUL is predicted in this study [15] using a stochastic hybrid system technique that considers the time-varying operational conditions that cause sensor deterioration. The operating condition discretization is done using continuous time Markov series and how the sensor degradation is affected is quantified by the degradation rate. The signal jumps in the state space are constructed using a non-linear Wiener process. A stochastic hybrid system (SHS) model is set up to consider the non-linearity of the attenuation, consisting of an interval continuous state variable and a discrete state variable. Using a nonlinear Wiener process, the continuous state variable, which consists of the degradation information, is expressed. The discrete state variable is expressed using a homogeneous continuous-time Markov chain (CTMC). Real-time updating was performed using a Bayesian updating model. It is suggested to predict future operating configurations using simulation-based Monte Carlo simulation to help find problems and prevent delays in warnings because different components may fail at different rates depending on the running conditions. The quick deterioration of machine tool axes was studied in a simulation study and on a dataset used for this model evaluation.

The paper [16] presents a case study of the proposed framework applied to transformers, using probabilistic prediction to predict future load conditions and fault prediction to predict future deterioration of transformers. This framework uses Bayesian inference to combine probabilistic and error prediction to achieve a more accurate and robust RUL prediction. In the area of energy and power, the concept of dynamic and stochastic energy is coming into picture for maintenance purposes, but the uncertainties are greater while considering the same. These uncertainties affect the operating conditions and lifetime management; therefore, it is very important to accurately integrate and propagate uncertainties. Different sources present at the lowest to upper level must be considered while considering uncertainties; otherwise, it will affect the lost to system scale. This leads to poor decision-making owing to a lack of knowledge in lifetime prediction. The state-of-the-art method proposed in integrates probabilistic forecasting with the experimental lifetime method. The uncertainties are expressed with the help of the PDF of the RUL predictions, which gives the RUL values for estimation in the future. The PDF are implemented using a Quantile Regression Forest and Quantile Gradient Boosting models, which aim to provide the best predictive power. This method was validated using two different power transformer datasets collected from power stations. Overall, this research represents a valuable benefaction to the field of predictive maintenance and asset management by providing a new framework to improve the accuracy and robustness of RUL predictions in uncertain event. The proposed framework has the potential to enhance the safety and capability of transformers and other equipment in various applications, making it a valuable tool in the electrical industry.

The difficulty of estimating the remaining life of a system continually monitored by sensors that deteriorate with time is resolved in the study [17]. Based on a degradation model for the system and sensors, this paper suggests a new technique to estimate how long such systems will last. Sensors are used for gathering accurate readings about the health of how a machine is working and to determine if any outlier or fault value is present, using this further evaluation is carried out. Sensors are used to obtain an exact reading of the process inside a component or system. Sometimes sensors are deployed at remote locations because of harsh environmental conditions such as vibration, rise in temperature, and radioactivity, and sensors gradually lose their functionality, resulting in incorrect readings. Owing to these incorrect values, the predicted output is misleading. These sensors can provide information about the condition of a system over its lifetime, allowing for the estimation of its RUL. The proposed methodology uses a stochastic degradation model to describe the sensor degradation process. This model takes into account various factors that contribute to system deterioration, such as usage, environmental conditions, and wear and tear. The authors have proposed a probability-based approach to estimate the parameters of the recession model. This involves maximizing the likelihood function of the observed data, which is a function of the model parameters. Overall, this study provides a comprehensive framework for estimating the remaining life of degraded systems using degradation sensors.

2.3 Hybrid Models

Hybrid modelling for RUL estimation combines the strengths of several methods, such as data driven and physics-based models, to enhance the accuracy of RUL prediction. This approach is particularly useful when available data are limited or when the error mechanism is complex and poorly understood. Hybrid models typically include two main components: data-driven and physics- based models. The data-driven model was trained on historical data to understand the relationship between sensor measurements and RUL. The physics-based model uses knowledge of the underlying physics of the system to model the deterioration process and predict the RUL. Figure 8 demonstrates flow diagram of the Hybrid model.

The data-driven model can be a simple linear regression model or a more composite deep learning model, such as a neural network. Physics-based modelling typically involves modelling the degradation process using laws and principles of physics. This may involve developing mathematical models based on system components and their interactions, or using empirical models based on physical experiments. The hybrid model combines predictions from data driven and physics based models to produce a final RUL estimate. This can be done using a weighted average, where the weights are determined based on the accuracy of each model, or using the Bayesian method, where the posterior distribution of the RUL is updated.

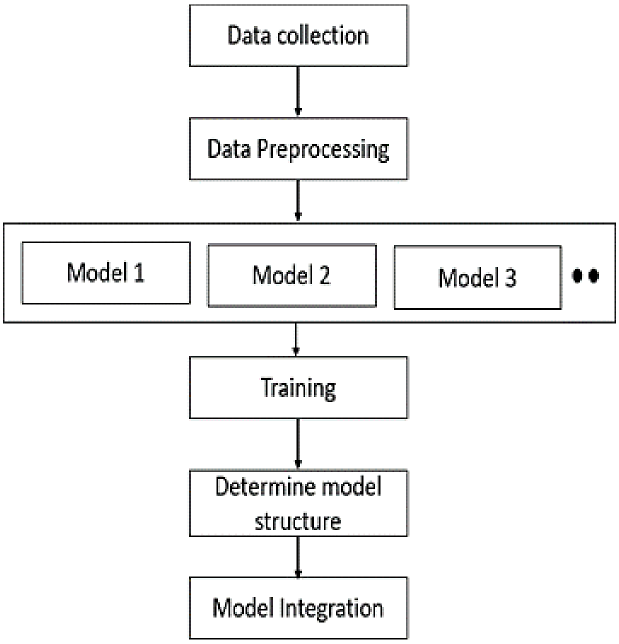

Fig. 8. Flow Diagram of Hybrid Model.

Using a combination of supervised machine learning model, artificial neural network architecture, and an advanced version of the neural network training (NBN) algorithm using a cumulative neural network design, Basheer Shaheen et al. [18] discussed a new technique to predict the remaining useful life of mechanical components. In this study, a novel data- driven technique was developed that can also be implemented for predictive maintenance to determine the RUL. This will eventually help reduce the downtime in the manufacturing industry. In particular, this article discusses an ANN-based technique used to predict the degradation process. Multilayer perceptron (MLP) is the most popular artificial neural network (ANN); however, to solve this problem, including more neurons, MLP is weak and inefficient Fully Connected Networks (FCN) and Arbitrary Connected Networks (ACNs) are more advanced and efficient than MLP. Cumulative ACN is the design of this item including 3 main layers: input layer, hidden layer and output layer. Component degradation increases over time, and to capture this monotonically increasing nature, the actual output of the last layer is added to the previous layer; This is called the cumulative network. The advantages of this model are that it consists of a smaller number of neurons, has precise prediction power, and requires less memory and a short training duration. One of the main advantages of the proposed method is that it does not require detailed understanding of the physics of the monitored system. This makes it more applicable to many mechanical components as well as systems where physics-based models are difficult to develop. The newly discovered model is efficient in processing many mechanical components of different decay laws with high accuracy compared to other networks. This can be used to accurately predict RULs and system failures.

In the paper [19], a novel approach to predict the remaining usable life (RUL) based on probabilistic prediction and deep reinforcement learning is presented. There are two forecasting methods: Deterministic and Probabilistic. In the deterministic forecast for each point in the future, a single value is generated by the forecast that matches the future output as closely as possible, whereas in the case of probabilistic forecasting, instead of forecasting a single value, the probability is assigned to every possible output. In other words, all future outputs are possible, but they are not likely. The proposed method uses a combination of deep reinforcement learning and probabilistic forecasting to predict RULs of aircraft components and proposes how deep reinforcement learning (DRL) can be used for maintenance planning, also based on the probability distribution of RUL. The probabilistic prognostic model provides a more nuanced and realistic view of the RUL of the component, which can help reduce the risk of unexpected failures. The method is applied to turbofan engines of the C-MAPSS dataset to determine the uncertainty in the RUL process, such as the Gaussian process, Bayesian process, deep ensemble, and Monto Carlo dropout, which is used in neural networks. In this study, Monte Carlo stall is used to estimate the probability distribution of RUL, the advantage of Monte Carlo is that it uses much lower computational cost. Regarding DRL, this is a new method in which maintenance is not scheduled based on a fixed threshold value; instead, they assume that degradation follows a combination of the gamma and Poisson processes. Overall, the paper presents a valuable contribution to the field of predictive maintenance, proposing a new method for RUL prediction using deep reinforcement learning and probabilistic prognosis. The proposed approach has the potential to improve the safety and efficiency of maintenance planning, resulting in significant cost savings and improved reliability.

Multiple sensors were used to record different readings on how to handle this complex data set, as discussed by Wang et al. [20], who proposed a method called Gated Graph Convolutional Network (GGCN), based on Graph Convolutional Network (GCN) and Gated Repetition Unit (GRU) to compute RUL where multiple Sensors are used to collect data. Currently, multi-sensors are used to monitor degradation in any industry, and these sensors have a potential relationship with each other. The methods currently present find it difficult to capture the uncertainty in sensors owing to their dynamic and complex system. Therefore, the two major concerns are how to mix these multisensory data and how to manage the uncertainty in data. Grid structured data, sequence structured data, or sequence grid structured data from multisensory signals currently used in neural networks; however, they cannot capture the dependencies between them. To solve this issue, a GGCN is developed, in which the first step is to construct graphs from multisensory signals as input to the prognosis model; the second step includes forming the gated graph convolutional layer to extract the degradation features, and finally, the extracted features are placed in the quantum regression layer to find the RUL. This method is evaluated on turbofan engine data sets, tool wear data sets and bearing data sets. Compared with existing deep learning methods, GGCN considers the correlation between sensor signals to capture degradation efficiently. The comparison of the results with the most advanced method confirmed the superiority of the GGCN-based prognostic method.

The article [21] discusses a combined method for predictive analysis of rotating machinery. The hybrid model includes a physics-based bearing model and a data- driven model for parameter prediction over time. The method used provides a simpler way to look at the variability of attributes. The model has been tested on heavy-duty locomotive engine bearings to predict wear and RUL, as well as temperature control parameters, for increased service life. Initially, using Archard's law and Reynolds's equation, a physics-based model was used, and using the data generated by it, the ANN was trained to provide high-speed RUL and wear predictions.

The RUL of a lithium ion battery (LIB) was calculated using a hybrid model in this study [22]. A convolutional neural network (CNN) and a Gaussian process regression (GPR) algorithm are both included in the combined model. First, depending on the features of the discharge capacity, CNN is used to estimate the preliminary life. The training data for lifecycle-based analysis was LIB, which has the most comparable deterioration trend. A double exponential model (DEM) is used to calculate the capacity of the chosen LIB. The DEM, as calculated by the first state, is employed as the mean value for the GPR method in the second phase. The RUL of the LIB is calculated using this model. Results were assessed using four long-period LIBs.

The paper [23] proposed a new method to predict the finite life of additively manufactured (AM) parts under fatigue load using a physics-based machine learning framework. AM is a developing technology that has various advantages, such as the capacity to create intricate geometrical designs and lower material waste. However, AM parts are known to have defects such as pores and cracks, which can significantly affect their fatigue life. Predicting the fatigue life of AM parts is important for ensuring their safe and efficient operation as well as informing decisions related to design and manufacturing. The proposed method involves using a combination of physics-based models and machine learning algorithms to predict the fatigue life of AM parts. Physics-based models were used to simulate the formation and development of defects in the AM part under fatigue loading. Machine learning algorithms are trained using data from physics- based models to predict the remaining fatigue life of the AM part. The model proposed in this paper is a physical information neural network (PINN) framework, which considers the structural features of materials that linear elastic fracture mechanics (LEFM) cannot consider. With the help of the novel semi-empirical model LEFM and Neural Network, a new model was developed. The model was evaluated using a dataset obtained from an AlSi10Mg alloy formed by selective laser melting, which contained structural characteristics and material fatigue experimental data. Validation is performed by K-fold cross-validation of PINN code generation. The PINN model is useful when the data set is not significantly large. The proposed method has the likely to enhance the safety and capability of AM parts in various applications as well as inform decisions regarding design and manufacturing.

3. DISCUSSION AND CONCLUSION

Although In our proposed research, we recognize that estimating the Remaining Useful Life (RUL) is a multifaceted challenge, particularly in the context of modern industrial settings characterized by Industry 4.0 technologies, complex machinery, and exponential data generation. Our approach to addressing this challenge involved a comprehensive methodology encompassing data collection, feature extraction, and the utilization of machine learning models. The summary of surveyed papers is given in Table 1.

Table 1. Summary of Applications by Machine Learning.

Model	Core	Advance NN Model-	Probabilistic Model
Reference	[1], [2], [5]	[7], [12], [9], [15]	[11], [18], [19], 16], [10], [3]
Task	RUL, SOH, Degradation model, Prognosis	RUL, Prognostic, Degradation trend, PHM	RUL, Degradation Model, Prognostic
Learning Process	Supervised	Supervised, Unsupervised	Unsupervised
Case Study	Lithium-ion battery, Landing aircraft,	Battery, Turbo fan engine, Bearing, Aircraft engines,	Oil industry tank, Bearing Dataset, Turbofan

Foundation of our RUL estimation methodology lies in the collection of appropriate data. This critical step involves decisions regarding sensor selection, deployment locations, and strategies tailored to environmental conditions. We acknowledge that the effectiveness of our RUL estimation hinges on the quality and relevance of the collected data. To ensure robustness, we meticulously planned and executed data collection strategies, considering factors such as sensor placement, data synchronization, and calibration.

The heart of any successful machine learning endeavour is feature extraction. This process involves identifying and selecting relevant features from the collected data. We acknowledge the pivotal role of feature extraction in determining the accuracy and effectiveness of our RUL estimation models. The feature selection process was driven by domain knowledge and data analysis, aiming to capture the most informative attributes that correlate with machinery degradation trends. We understand that the choice of features significantly impacts the predictive power of our models, and we have strived to select the most pertinent ones for our analysis.

In our pursuit of accurate RUL estimation, we employed a diverse set of machines learning models, including both core and advanced approaches. These models serve as the computational backbone of our methodology, translating raw sensor data into actionable RUL predictions. We recognize the importance of model selection in addressing the unique challenges posed by complex industrial systems. Our choice of models reflects a balance between well-established methods and state-of-the-art techniques that offer superior performance and robustness.

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