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OPTIMISING RAILWAY ASSET MAINTENANCE WITH REAL TIME PROGNOSTICS AND HEALTH MANAGEMENT IN THE ABSENCE OF RUN TO FAILURE DATA

[1]Dr. M. RAMASUBRAMANIAN, [2]MV. SRAVANI, [3]S. ISHWARYA, [4]M. NIKITHA

[1]Professor, Department of Computer Science and Engineering, Sridevi Women's Engineering College, Hyderabad, India

Email: ramanmass01@gmail.com

[2,3,4,]B.Tech Student, Department of Computer Science and Engineering, Sridevi Women's Engineering College, Hyderabad, India

ABSTRACT

Prognosis is a challenging technology that aims to accurately predict and estimate the remaining useful life of a component or system in order to enhance its reliability and performance. Although prognosis research for predictive maintenance is a well-researchedtopic, practical examples of successful prognostic applications remain scarce. This is due to the lack of available run-to-failure data to build the prediction model as maintenance is usually conducted regularly to avoid significant defects. This project proposes a novel prognosis method that can be applied to real-world railway maintenance planning without employing run-to- failure data. The key idea is that the fault severity assessment and approximate remaining time prediction are often all that is needed in order to plan maintenance. Firstly, using motor current signals, a degradation indicator on railway doorsystems is generated based on the dynamictime warping method to measure similarity between typical normal and faulty behaviour. Then, the K-means algorithm is applied to assess fault severity, followed by the representative time estimation for each level of fault severity. This estimation thus allows the remaining time prediction until reaching the critical fault severity level without using run-to- failure data. As a result, the proposed method enables predictive maintenance planning for railway door systems. In addition, the fault severity threshold can be updated by additional operational data, enabling the remaining time prediction to be more reliable. Furthermore, the proposed method can be applied to conventional railway assets and other electro-mechanical actuators as motor current signals are primarily available from the controller or motor drive without additional sensors.

Keyword: Euros. Prognosis is a challenging technology that aims to accurately predict and estimate the remaining useful life (RUL) of a component or system in order to enhance its reliability and performance.

INTRODUCTION

Prognostics and Health Management (PHM) is an all- encompassing technology that enables engineers to turn data and health states into information that can be used to increase the knowledge of a system and provide a strategy to maintain the system in its originally intended function. Whilst PHM originated in the aerospace industry, it is now being explored in

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many applications in industries such as manufacturing, automotive, railway, and heavy industry. There are many benefits to employing PHM, such as significantly reducing support and operating costs. For example, an unexpected one-day stoppage in the machinery industry may incur costs as high as up to 100,000 to 200,000 Euros. Prognosis is a challenging technology that aims to accurately predict and estimate the remaining useful life (RUL) of a component or system in order to enhance its reliability and performance. RUL is the duration between the current time and the time at which the forecasted health level reaches a predefined failure threshold, which is when the system cannot continue fulfilling its intended functions. During the early stages of health monitoring technology, traditional applied technologies focused on detecting and isolating failures. As the demand for Condition-Based Maintenance (CBM) increased, the idea of using RUL as a prognostic failure prediction technique grew in popularity. Current prognostic approaches can be categorized into two major categories, namely physics-based models and data driven approaches.

The key idea is that the fault severity assessment and approximate remaining time prediction are often sufficient for decision making in maintenance planning, such as scheduling work, ordering parts and other specialised resources, and withdrawal from service. Therefore, this research aimed to establish a practical prognosis methodology instead of estimating accurate RUL. Firstly, a degradation indicator on railway door systems is generated using motor current signals based on the dynamic time warping (DTW) method to measure the similarity between typical normal and faulty door systems behaviour. Then, the K-means algorithm is applied to assess fault severity, followed by the representative time estimation for each level of fault severity. This estimation enables the remaining time prediction until critical fault severity to be calculated without using RTF data. It should be noted that although methods exist to calculate fault severity and diagnosis by using the DTW method and K-means algorithm this project proposed prognosis method is novel as it is the first method that does not use RTF data. The main contributions of the projecct are summarized as follows: 1. This project proposes a novel prognosis method that can be applied to real-world railway maintenance planning that does not use RTF data. 2. The fault severity threshold can be updated by including additional operational data, enabling the remaining time prediction to be more reliable. 3. The proposed method can be applied to conventional railway assets and other EMAs as motor current signals are primarily available from the controller or motor drive without additional sensors.

RELATED WORK

Current status of machine prognostics in condition-based maintenance.

Condition-based maintenance (CBM) is a decision-making strategy based on real-time diagnosis of impending failures and prognosis of future equipment health. It is a proactive process that requires the development of a predictive model that can trigger the alarm for corresponding maintenance. Prognostic methodologies for CBM have only recently been introduced into the technical literature and become such a focus in the field of maintenance research and development. There are many research and development on a variety of technologies and algorithms that can be regarded as the steps toward prognostic maintenance. They are needed in order to support decision making and manage operational reliability. In this paper, recent literature that focuses on the machine prognostics has been reviewed. Generally, prognostic models can be classified into four categories: physical model, knowledge-based model, data-driven model, and combination model. Various techniques and algorithms have been developed depending on what models they usually adopt. Based on the review of some

typical approaches and new introduced methods, advantages and disadvantages of these methodologies are discussed. From the literature review, some increasing trends appeared in the research field of machine prognostics are summarized. Furthermore, the future research directions have been explored. Keywords Condition- based maintenance-Prognostics.

A new hybrid prognostic methodology

Methodologies for prognostics usually centre on physics-based or data- driven approaches. Both have advantages and disadvantages, but accurate prediction relies on extensive data being available. For industrial applications, this is very rarely the case, and hence the chosen method's performance can deteriorate quite markedly from optimal. For this reason, a hybrid methodology, merging physics-based and data-driven approaches, has been developed and is reported here. Most, if not all, hybrid methods apply physics-based and data-driven approaches in different steps of the prognostics process.

The presented technique combines both methods in forecasting, and integrates the short-term prediction of a physics-based model with the longer-term projection of a similarity-based data-driven model, to obtain remaining useful life estimation.

The proposed hybrid prognostic methodology has been tested on two engineering datasets, one for crack growth and the other for filter clogging. The performance of the presented methodology has been evaluated by comparing remaining useful life estimations obtained from both hybrid and individual prognostic models. The results show that the presented methodology improves accuracy, robustness and applicability, especially in the case of minimal data being available.

Review of hybrid prognostics approaches for remaining useful life prediction of engineered systems, and an application to battery life prediction

Prognostics focus on predicting the future performance of a system, specifically the time at which the system no long performs its desired functionality, its time to failure. As an important aspect of prognostics, remaining useful life (RUL) prediction estimates the remaining usable life of a system, which is essential for maintenance decision making and contingency mitigation. A significant amount of research has been reported in the literature to develop prognostics models that are able to predict a system's RUL. These models can be broadly categorized into experience-based models, date-driven models, and physics-based models. However, due to system complexity, data availability, and application constraints, there is no universally accepted best model to estimate RUL. The review part of this paper specifically focused on the development of hybrid prognostics approaches, attempting to leverage the advantages of combining the prognostics models in the aforementioned different categories for RUL prediction. The hybrid approaches reported in the literature were systematically classified by the combination and interfaces of various types of prognostics models. In the case study part, a hybrid prognostics method was proposed and applied to a battery degradation case to show the potential benefit of the hybrid prognostics approach.

METHODOLOGY

- **Data Preprocessing**

  Handling missing values, formatting, and scaling data.

- **DTW Calculation Function**

  A function to calculate Dynamic Time Warping (DTW) similarity between time series data points.

- **KMeans Clustering**

  Utilizing the KMeans algorithm to cluster the DTW similarity values into severity assessment levels.

- **Visualization**

  Plotting the current signals and clusters to observe patterns and severity levels.

- **Lifetime Calculation**

  Determining the remaining useful lifetime (RUL) using the clusters.

- **Performance EvaluationComparing the performance of KMeans clustering with and without parameter tuning.**

- **Data Handling**

  Loading and managing datasets using Pandas.

- **External Libraries**

  Utilizing libraries like NumPy, tslearn, and Matplotlib for numericalcomputations, time series analysis, and visualization respectively.

- **Model Evaluation**

  Assessing the effectiveness of the clustering algorithm in identifying severity levels and predicting remaining lifetime.

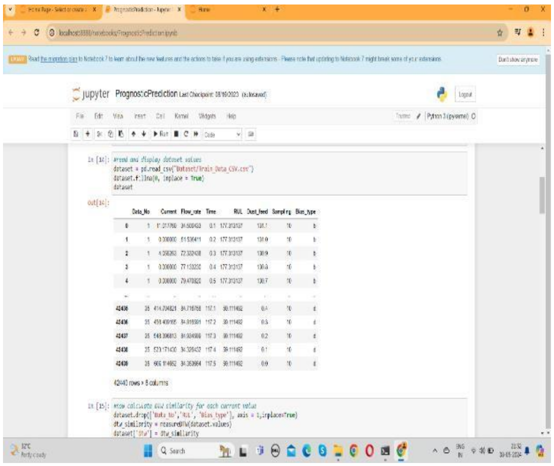
- **Optimization**

  Tuning KMeans parameters to improve clustering performance.

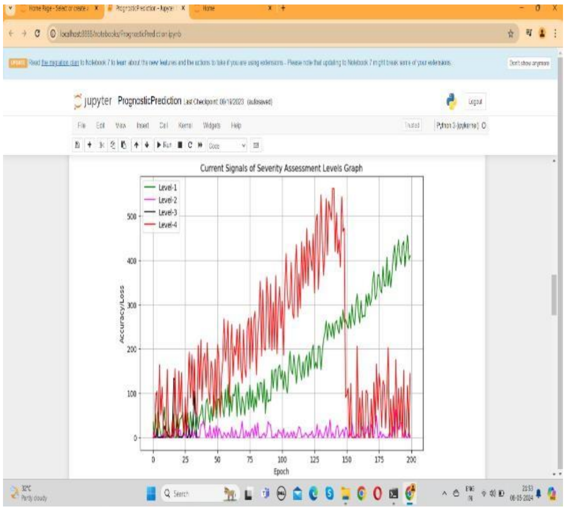
RESULTS

- To implement this project we have used JUPYTER notebook and below are the code and output screens.

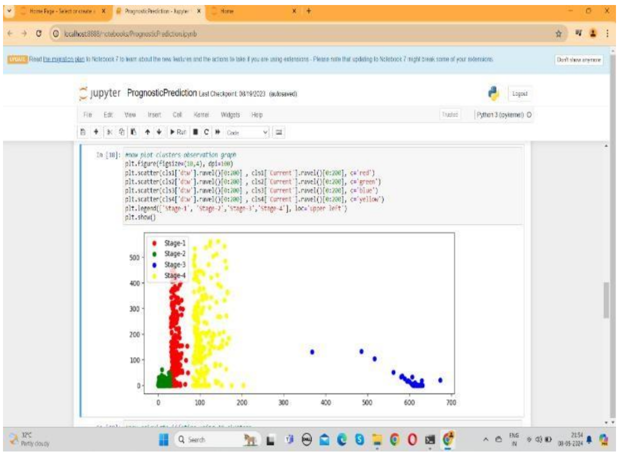
- In above screen we have imported require python classes and packages and then defining function to calculate DTW similarity.



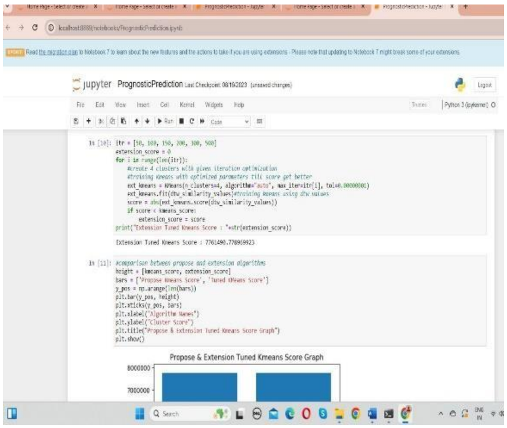
- In above screen loading and displaying dataset values.
- These dataset values are loades through a CSV file.



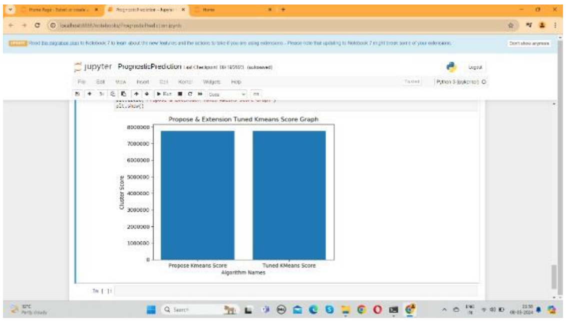
- Above is the 4 cluster graph where x- axis represents MOTOR current index and y-axis represents motor current values.
- Different line represents different values in cluster and in above graph wecan see cluster in magenta colour line has normal values without any much gap.
- In black, green and red colour lines cluster we can see lines are having too much up and drops so it contains faulty values. So by using K-means we can see which cluster values are faulty
- In below screen we are plotting stages of 4 clusters



- In above screen each colour circle represents one stage.
- The ending and starting difference of each cluster values will be consider as Lifetime and after finding median and subtracting above cluster values we will get below lifetime for each stage.



- In above screen we are tuning KMEANS with various iterations.
- Then in last we got KMEANS with lesser score and this less score KMEANS object is the optimized KMEANS.



- In above graph x-axis represents algorithm names and y-axis represents SCORE and in both algorithm extension KMEANS got less score.

CONCLUSION

Implementing real-time prognostics and health management systems for railway assets without relying on run-to-failure data offers significant advantages, including enhanced safety through proactiveidentification of potential failures, increased asset availability by minimizing unplanned downtime, cost savings from optimized maintenance scheduling, data- driven decision-making for asset management, environmental benefits through energy-efficient operations, and adaptability through continuous learning and improvement. Despite the challenges of setup and implementation, such systems represent a pivotal shift towards more reliable, efficient, and sustainable railway operations, promising a future of safer, more reliable transportation networks.

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