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RESEARCH ARTICLE

Real-Time Prognostics and Health Management Without Run-to-Failure Data on Railway Assets

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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-researched topic, 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 paper 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 door systems is generated based on the dynamic time 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.

INDEX TERMS Fault detection, prognosis, prognostics and health management, PHM, signal processing, remaining useful life, railway, door systems, linear actuator, electro-mechanical actuators, EMAs.

I. 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 many applications in industries such as manufacturing, automotive, railway, and heavy industry [1]. 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 [2]. Furthermore, PHM also significantly increases safety as devastating accidents are more likely to occur from inadequate maintenance. One example of this is an incident on 10th May 2002 when a train travelling from London to Norfolk in the UK derailed at Potters Bar railway station, causing seven deaths and injuring over 70 people. The derailment was due to a points failure; one of the main factors being that the points had been poorly maintained [3]. This incident demonstrates the fatal

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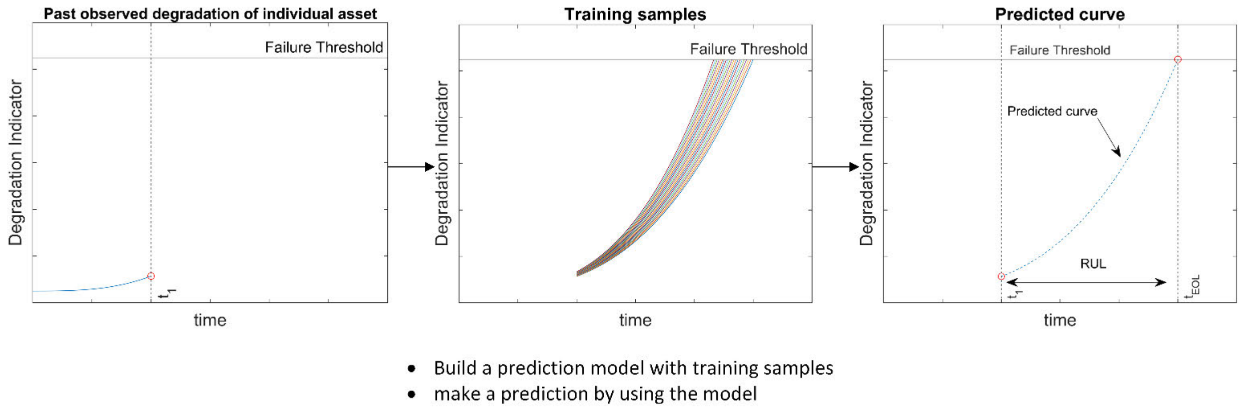

FIGURE 1. Typical conventional prognosis method based on data-driven approaches.

consequences that can arise from insufficient and inappropriate maintenance as well as the likely loss of public trust in the industry.

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 [4]. 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 focussed 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 categorised into two major categories, namely physics-based models and data-driven approaches. A typical physics-based models' prognostic strategy consists of dynamic models to perform the prediction function of the system's future state. Physics-based approaches provide technically comprehensive solutions that have been used widely to understand the failure progression [4]. These models assume that an accurate mathematical model for degradation can be constructed from the first principle [5]. Additionally, model parameters may be identified using empirical data obtained from specifically designed experiments [6]. Then, the physics-based models can be used to determine the system's life usage by calculating the physics parameters for the system at that particular time. Once the current physics parameters have been identified, the model can predict future conditions based on historical conditions using stochastic techniques. Some of the most-used examples include fatigue crack propagation modelling [7], battery capacity modelling [8], centrifugal pump degradation modelling [9], thermal processing unit degradation [10], pneumatic valve modelling [11], and DC-DC converter system level degradation model [12]. However, physics-based models largely rely on employing expert domain knowledge, and the models are also component-specific or system-specific, which means that they cannot be applied to other types of components or systems where the physics of failure mechanism differs. Moreover, industrial machinery systems contain many components interconnected with various uncertainties, which makes the physics-based modelling approach of limited value in predictive maintenance.

On the other hand, data-driven approaches use historical run-to-failure (RTF) data to build a statistical, machine learning, or deep learning model. Data-driven approaches are divided into two categories: statistical models and machine learning models.

Statistical approaches construct models by fitting a probabilistic model to the data without any engineering or physical principle knowledge. These approaches rely on statistical models and the observed data to support the prediction of the RUL. X.S. Si et al comprehensively reviewed the statistical approaches for RUL estimation [13]. On the contrary, machine learning models attempt to recognise complex patterns and make a prediction based on key historical degradation information. Machine learning approaches are adaptable to situations where expert domain knowledge is unavailable. A typical prognosis method based on data-driven approaches is described in Figure 1. Firstly, a prediction model is built with RTF training samples acquired during machinery operations. Then, a future degradation curve is estimated by the prediction model. Once a failure threshold can be determined, the RUL can also be estimated with the predicted curve and the failure threshold. Prognosis studies have been conducted based on machine learning and deep learning, including neural network [14], [15], logistic regression [16], deep neural network [17], [18], autoencoder [19], [20], deep belief network [21], long short-term memory [22], [23], [24] and generative adversarial network [25]. The significant advantage of data-driven approaches is that it does not require expert domain knowledge and understanding of the failure mechanism of the complex machinery behaviour if a sufficient amount of RTF dataset is available. Therefore, this approach has gained attention with academic researchers and industrial engineers as the amount and availability of data increases.

However, the serious limitation of the data-driven approach is the lack of available RTF training samples to build a prediction model as maintenance is usually conducted regularly to avoid significant defects in order to meet customer demand and social responsibility. In addition, it is also difficult to determine the failure threshold, which is described in Figure 1, as the end-of-life of machinery is hardly observable due to the conservative maintenance upkeep. Thus, the RUL with the conventional data-driven approaches is unpredictable during the model training phase until enough RTF data is available and the failure threshold can be determined. In other words, conventional prognosis methods can be impractical due to insufficient RTF data. This is a major challenge, and few studies can be found that attempt to overcome this hurdle.

To tackle the issue, this paper proposes a novel prognosis method that can be applied to real-world railway maintenance planning without employing RTF data. 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 [26], [27], this paper's proposed prognosis method is novel as it is the first method that does not use RTF data. The main contributions of the paper are summarised as follows:

1. This paper 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.

The remainder of this article is organised as follows: section II provides a brief background of relevant previous research; the proposed methodology, result, and discussion regarding fault severity assessment and prognosis are given in sections III and IV; and section V concludes the paper's findings.

II. LITERATURE REVIEW

The major challenge related to the lack of RTF data to build RUL prediction models remains to be overcome. Although there are a few studies that attempt to solve this issue, all still require a certain amount of RTF data. This is not a complete solution and still poses elements of impracticality. For instance, some research proposes data augmentation techniques by using historical suspension condition monitoring data to increase training data in order to address the lack of RTF data [28], [29], [30]. Suspension data refer to condition monitoring data acquired from the very beginning of an engineered system's lifetime until planned inspection or maintenance when the system is taken out of service [30]. For example, the training data is augmented as virtual RTF data created by using obtained RTF data and suspension data with the DTW method [28]. Z. Tian et al and C. Hu et al propose artificial neural networks [29] and semi-supervised co-training approaches [30], respectively. These proposed methods are used to increase labelled training datasets with suspension historical data and RTF data. Even though they show extremely accurate RUL, a certain amount of RTF data is still required to build initial data-driven models to amplify training datasets. That requirement makes practical prognosis application still challenging at the initial stage as little RTF data is available in many engineered systems. In another example, the prognostic approach utilising the accelerated life testing (ALT) degradation data is proposed to convert the ALT data to field loading conditions [31]. However, this approach requires ALT data acquisition under different loading conditions to obtain actual field condition data from them in advance, which requires significant experiments and is therefore not practical. Thus, the major challenge related to the lack of RTF data remains to be addressed, particularly at the initial stage of practical prognosis application where RTF data is unavailable.

Furthermore, there is lacking prognosis research on door systems and electro-mechanical actuators (EMAs). This paper uses operational railway door system datasets as an example. The railway door systems use electric linear actuators. For example, the diagnosis and prognosis method with a particle filter for EMAs was presented, focusing on a windings fault by using physics-based dynamic models [32]. However, the developed model is a component-specific model and hence cannot be applied to other types of components or faults in which the physics of failure mechanism differs, such as door systems. C. S. Byington et al propose a data-driven methodology to estimate the state of health and predict the remaining useful life of aircraft actuator components with fuzzy logic [33], which requires a predefined set of rules based on expert engineering knowledge and Kalman filters. E. Balaban et al have conducted experiments with a flyable electromechanical actuator testbed (FLEA) and predicted RUL with Gaussian process regression (GPR) using motor temperature [34], [35]. Y. Zhang et al demonstrated another RUL prediction example with weighted bagging GPR (WB_GPR) based on data-driven approaches by using the experimental dataset by NASA [36]. P. C. Berri et al established a RUL prediction workflow with support vector machine (SVM) using

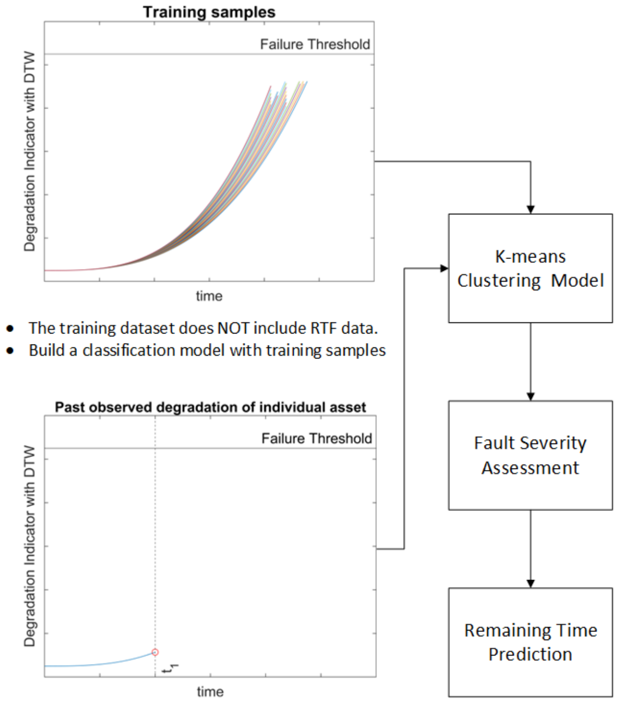

FIGURE 2. **The proposed prognosis method to predict the remaining time.**

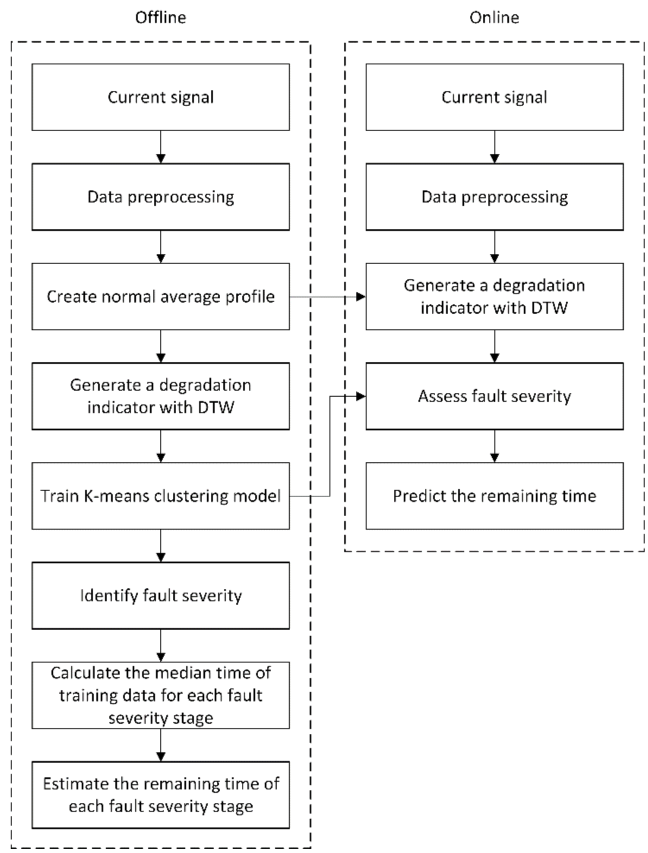

FIGURE 3. **The proposed workflow to predict the remaining time for train doors.**

health status estimation with multi-layer perceptron (MLP) [37], [38]. J. Yan et al also developed a logistic regression-based approach for degradation evaluation and RUL prediction of elevator door open-close cycles [16]. More recently, A. Caliwag et al applied deep neural network techniques for fault occurrence prediction on the entire train system, including door systems [39]. Despite the successful outcomes of these approaches, the proposed RUL predictions still require enough RTF data to build the model. Thus, a deficiency of RTF data limits its application for practical purposes.

III. PROPOSED METHODOLOGY

A. PROPOSED WORKFLOW

The proposed method and workflow to predict the remaining time are shown in Figure 2 and Figure 3. The workflow is divided into two procedures: offline and online. In the offline procedure, current signals acquired from railway assets are used as training datasets to build an unsupervised clustering model to assess the fault severity level and estimate the remaining time. In this paper, the remaining time refers to the duration from the certain fault severity stage to the critical fault severity stage. Critical fault severity is when a system has reached a point where maintenance cannot be delayed; it is the last warning point for planning maintenance before failure. In this approach, time-series current signals are pre-processed to be aligned and eliminate noise using a low pass filter. Then, pre-processed data is used to create a typical normal current profile by averaging a hundred normal profiles, followed by the generation of degradation indicators with the DTW method. Then, the K-means unsupervised machine learning algorithm is trained with the degradation indicators to create fault severity clusters. If maintenance records were available, whose information is unavailable in this research, the critical fault severity stage could be identified using created fault severity clusters and maintenance records. For example, suppose a fault severity cluster A is equivalent to the cluster just before door maintenance activity based on maintenance history. In that case, the fault severity cluster A becomes the critical fault severity stage. The median time of training data belonging to each fault severity stage with the K-means method is calculated. This calculation enables the remaining time prediction, details of which are described in Section IV.

The clustering model created offline is implemented in the online procedure to assess the fault severity and predict remaining time in real-time. First, the current signals are pre-processed and the degradation indicator is generated in the online with the DTW method. The typical normal current profile created offline is employed in the online procedure to calculate the DTW distances. Then, the online fault severity assessment is executed with the K-means clustering model built offline once one door operation is completed, followed by the remaining time prediction that thus helps machinery to be maintained before it breaks down.

The proposed workflow offers significant advantages in terms of practical real-time prognostics and health management. Firstly, the proposed method can be applied to real-world railway maintenance planning as the remaining

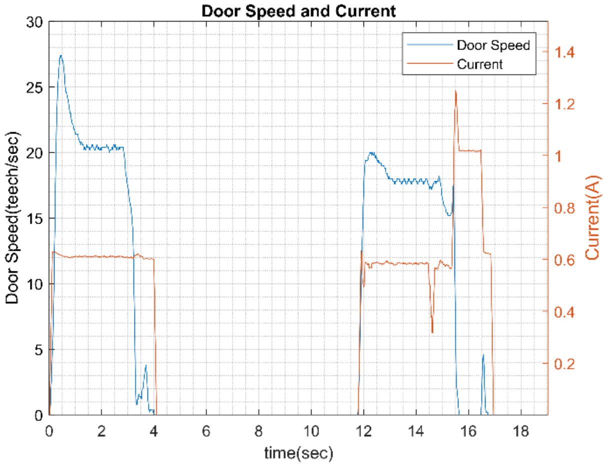

FIGURE 4. **Door speed and current signals.**

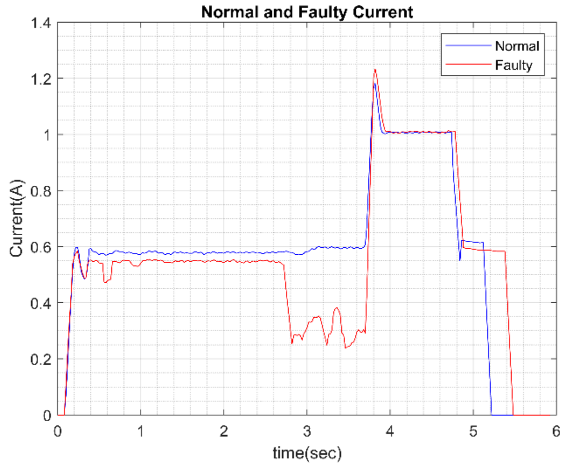

FIGURE 5. **The normal and faulty current signals.**

time can be predicted in real-time without using RTF data. This solves the current issue of needing sufficient RTF data to build a prediction model. Secondly, the fault severity threshold can be updated by using additional operational data. The fault severity threshold refers to the critical fault severity stage, meaning that maintenance should be conducted before reaching that severity level. As a result, the remaining time can be more reliable. Additionally, the proposed method can also 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, which is also beneficial for practical prognostic health management systems.

B. SEVERITY ASSESSMENT

1) DATA ACQUISITION

This study uses large real-world datasets of door systems in railway assets to build a prediction model. Specifically, this paper focuses on electric doors, composed of a voltage power source, a DC motor, a door control unit (DCU), a transmission, and door leaves. In short, a DC motor, powered by a voltage source and controlled by a DCU, can output the specified shaft angular velocity and torque, which are transmitted to transmission so that the door leaves can move in a pre-designed manner [40]. The door data, which consists of current and encoder signals, is collected through the communication port from the DCU at a frequency of 50 Hz. The data is acquired from one specific door of a train during actual railway service operation and include 6,039 door-opening and closing operations. A time lag is often observed between the motion profile and the current. To align the time series, the DTW method is used for the first alignment. The low pass filter is applied on a window of 0.25 seconds, representing five consecutive measurement time intervals to reduce the noise carried by both current and encoder signals.

2) AN EXAMPLE OF THE SIGNAL PROFILE

An example of the signal profile of the opening and closing operations is shown in Figure 4. In the opening profile, the speed and current increase steadily up to a maximum, followed by a slight curve, and then decrease to zero. The closing profile follows a similar pattern but has two main differences in the current. The first main difference is that the peak in the closing profile is lower than the opening. The second key difference is that there is an abrupt change at the end of the closing profile, followed by a slight bump in the speed, which promotes pushing the door to its maximum reachable position where a locking process can be triggered [41].

In this research, current signals in the closing operation are used for fault severity classification and prediction of the remaining time. The example of the normal and faulty current signal is shown in Figure 5. The normal current signal has flat curves from 2.6 sec to 3.7 sec, while there are negative peaks and fluctuations in the dataset of the faulty current signal.

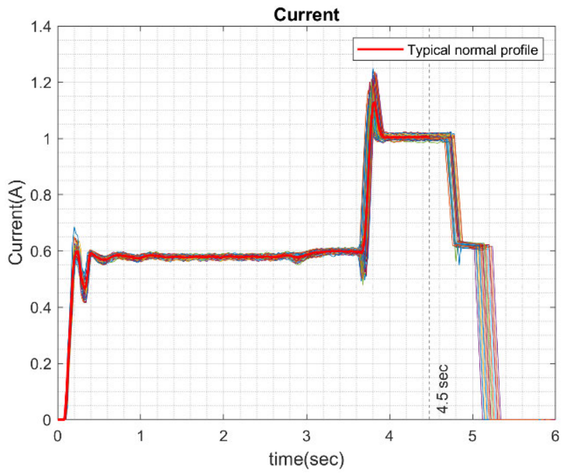

FIGURE 6. **The typical normal current profile.**

3) DYNAMIC TIME WARPING METHOD

The DTW method is applied to generate a condition indicator by using a typical normal current profile. The average of 100 normal profiles is calculated and used in order to create the typical normal current profile, as shown in Figure 6. It should be noted that an average is taken from normal current profiles from 0 sec to 4.5 sec to create the typical normal current profile as faulty characteristics can emerge in this range, as shown in Figure 5. In addition, the profiles over 4.5 sec slightly differ from each other despite the difference having no correlation with fault, so it is essential to eliminate these profiles over 4.5 sec in this example dataset. Afterwards, a degradation indicator on railway door systems is generated based on the DTW method to measure similarity between two temporal sequences: a typical normal current profile and an operation of door systems.

The DTW method is one of the most widely-used algorithms for measuring the similarity between two temporal sequences that may vary in time [42], which was originally used in speech recognition [43].

Given are the two time series of length N and M:

$$\mathbf{X} = \{x_1, x_2, \ldots, x_i \ldots, x_N\}, \quad for\ i \in [1:N] \tag{1}$$

$$\mathbf{Y} = \left\{y_1, y_2, \ldots, y_j \ldots, y_M\right\}, \quad for\ j \in [1:M] \tag{2}$$

The x_i and y_j represent values at the point i and j of $\mathbf{X}$ and $\mathbf{Y}$, respectively. In this research, these two sequences represent time-series data, such as the current signals of door systems. To compare two time series, N-by-M cost matrix is defined, and its element is the distance between x_i and y_j, which is expressed by:

$$C(n, m) = c\left(x_i, y_j\right) \tag{3}$$

$$c\left(x_i, y_j\right) = |x_i - y_i| \tag{4}$$

Generally, $c(x_i, y_j)$ becomes small if x_i is similar to y_j, however if they are not similar to each other, $c(x_i, y_j)$ becomes large. In this research, Euclidean distance is chosen to calculate the cost, as shown in equation (4). Then, the goal is to minimise overall cost and find an optimal match between $\mathbf{X}$ and $\mathbf{Y}$. An (N, M)-warping path means a sequence $p = (p_1, p_2, \ldots, p_l, \ldots, p_L)$ with $p_l = (n_l, m_l) \in [1: N] \times [1: M]$ for $l \in [1: L]$, which meets the following three constraints [44].

1. Boundary constraint: $p_1 = (1, 1)$ and $p_L = (N, M)$
2. Monotonic constraint: $n_1 \leq n_2 \leq \ldots \leq n_L$ and $m_1 \leq m_2 \leq \ldots \leq m_L$
3. Step size constraint: $p_{l+1} - p_l \in \{(1, 0), (0, 1), (1, 1)\}$ for $l \in [1: L-1]$

The boundary constraint enforces that the first and last element of $\mathbf{X}$ must be the first and last element of $\mathbf{Y}$. This means that the sequence of $\mathbf{X}$ needs to be aligned with the entire sequence of $\mathbf{Y}$. The monotonicity constraint is the requirement of the appropriate match between two sequences as an essential pattern of time-series sequence is continuity. The third step's size restriction requires that all elements in $\mathbf{X}$ and $\mathbf{Y}$ need to be used and that there are no duplications in the alignment.

The total cost $c_p(\mathbf{X}, \mathbf{Y})$ of a warping path p is calculated by accumulating each costs $c(x_{nl}, y_{ml})$ along the path as follows:

$$c_p(\mathbf{X}, \mathbf{Y}) = \sum_{l=1}^{L} c(x_{nl}, y_{ml}) \tag{5}$$

Suppose a warping path p^* is an optimal warping path between $\mathbf{X}$ and $\mathbf{Y}$, having minimal total cost among all possible warping paths, then the DTW distance DTW($\mathbf{X}$, $\mathbf{Y}$) between $\mathbf{X}$ and $\mathbf{Y}$ is defined as the total cost of p^*:

$$\begin{aligned} DTW(\mathbf{X}, \mathbf{Y}) &= c_{p^*}(\mathbf{X}, \mathbf{Y}) \\ &= \min\{c_p(\mathbf{X}, \mathbf{Y}) | p\ is\ an\ (N, M) \\ &\quad - warping\ path\} \end{aligned} \tag{6}$$

The optimal path p^* can be selected based on the cumulate cost matrix $\mathbf{D} \in \mathbb{R}^{N \times M}$, which satisfies the following identities:

$$D(n, 1) = \sum_{k=1}^{n} c(x_k, y_1) \quad for\ n \in [1:N] \tag{7}$$

$$D(1, m) = \sum_{k=1}^{m} c(x_1, y_k) \quad for\ m \in [1:M] \tag{8}$$

$$\begin{aligned} D(n, m) &= c(x_n, y_m) \\ &\quad + \min\{D(n-1, m-1), D(n-1, m), \\ &\quad D(n, m-1)\} \quad for\ 1 < n \leq N\ and\ 1 < m \leq M \end{aligned} \tag{9}$$

The first row and column of matrix $\mathbf{D}$ are calculated with the cumulative cost along the row and column, respectively. The $D(n, m)$ for $1 < n \leq N$ and $1 < m \leq M$ are calculated with the sum of $c(x_n, y_m)$ and the smallest cumulated cost among adjacent elements, which are $D(n-1, m-1)$, $D(n-1, m)$, $D(n, m-1)$. Once the cumulative cost matrix $\mathbf{D}$ is calculated with the above equation, the optimal path p^* can be determined recursively starting from $p_L = (N, M)$ to $p_1 = (1, 1)$, which are from end to start of sequences. Next, when $p_l = (n, m)$ has been computed, the next point p_{l-1} can be determined as:

$$p_{l-1} = \begin{cases} (1, m-1) & if\ n = 1 \\ (n-1, 1) & if\ m = 1 \\ argmin\{D(n-1, m-1), & \\ D(n-1, m), D(n, m-1)\} & otherwise \end{cases} \tag{10}$$

As a result, the optimal path p^*, which can be the best alignment between two time-series sequences, is found with DTW. Furthermore, the optimal path offers minimal total distance among all possible warping paths, which can be used as a similarity between two time series data.

In this research, the degradation estimation is carried out based on the DTW distance between the typical normal profile described in Figure 6 and the current signals of closing operations, which has the same range as that of a typical normal profile, from 0 sec to 4.5 sec.

4) K-MEANS CLUSTERING

K-means clustering is one of the most well-known unsupervised partitional clustering algorithms because of its easy-to-implement nature, simplicity, efficiency, and empirical success [45]. The K-means assigns n training feature vectors to exactly one of the k clusters. This method has been used in

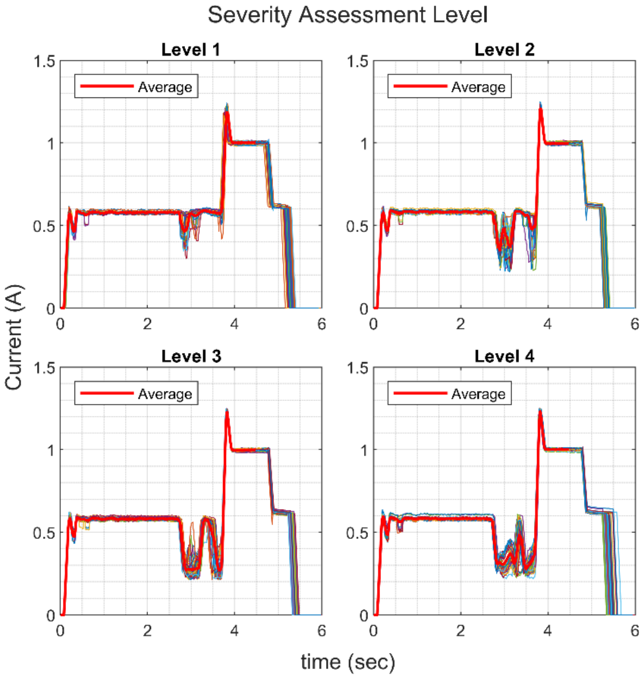

FIGURE 7. Current signals of severity assessment levels.

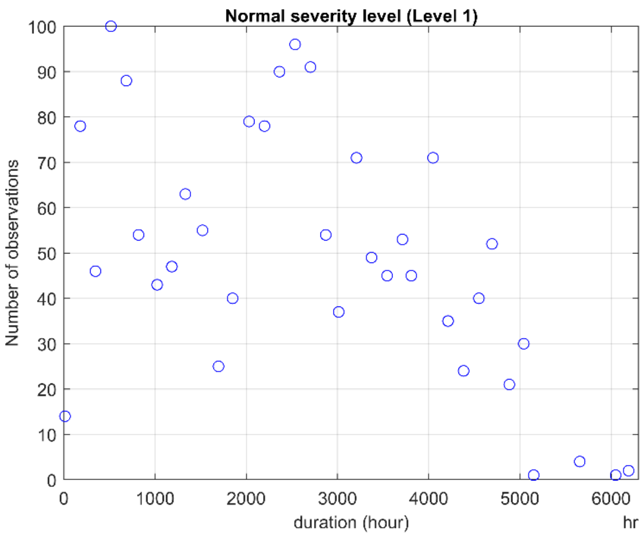

FIGURE 8. The number of observations of normal severity level per week.

a lot of previous research as industrial data usually contains both normal and abnormal data in high-dimensional space, making it difficult to manually segregate it [41], [46]. The steps for K-means clustering are the following [47]:

1. Choose k centroid (initial cluster centre) and use the K-means ++ algorithm for cluster centre initialization [48].
2. Compute distances between cluster centres and training feature vectors.
3. Assign each training feature vector to the cluster with the closest centre (this step is called a Batch update).
4. Compute the average of the training feature vectors in each cluster to obtain k new cluster centres.

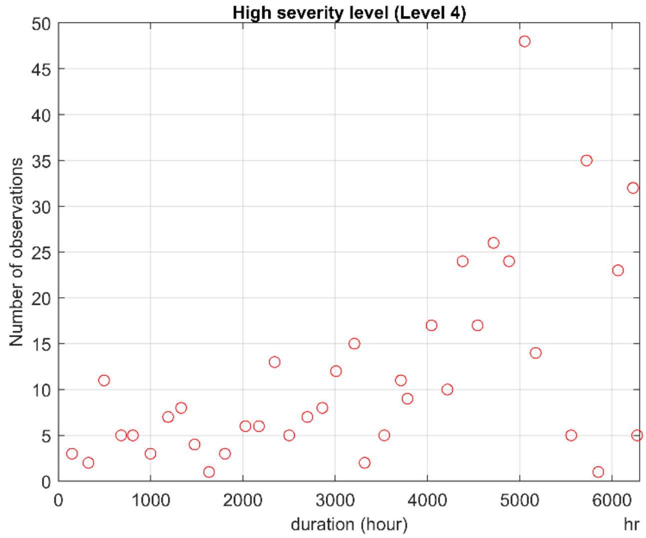

FIGURE 9. The number of observations of high severity level per week.

5. Repeat steps 2, 3, and 4 until the centres do not change their values.
6. Repeat steps from 1 to 5 ten times. The clustering result with the lowest sum of squared distances between cluster centres and training feature vectors is selected.

In this research, the K-means algorithm is employed for fault severity classification based on the degradation estimation calculated by the DTW method.

IV. RESULT AND DISCUSSION

This section presents the outcomes of fault severity assessment and the remaining time prediction.

A. FAULT SEVERITY ASSESSMENT RESULT

This research first gathers and analyses datasets from a railway asset. Then, four clusters are created using the K-means clustering algorithm with the DTW distance, which means that the operational data is separated into four clusters. Four degradation levels are typically used in the railway industry, which are, for instance, normal (green), moderate (amber), severe (orange), and extreme (red). As shown in Figure 7, in which the average signals for each level are drawn in bold and red, current signals for level 1 have relatively flat curves from 2.0 sec to 3.8 sec, while there are large fluctuations and negative peaks for levels 2, 3, and 4. These represent normal and faulty characteristics, as described in Figure 5.

It is worth noting that the fluctuations and magnitude of negative peaks become more extensive as the severity assessment level rises. To analyse the normal and high severity level characteristics, level 1 and level 4 are assumed to be normal and high severity levels, respectively. As described in Figure 8, the number of observations of the normal severity level per week, which is from level 1, steadily decreases over time, while the high severity level, level 4, rises continuously, as shown in Figure 9. The component should degrade over time; this is reflected in the trend in Figure 8 and Figure 9. Thus, this result reveals that levels created by the K-means algorithm with DTW distance can represent the level of fault severity.

The above result is also intuitively rational as the DTW distance also demonstrates how far off a door systems operation is from normal behaviour. Hence, the DTW distance can represent fault severity. In this research, the DTW method can be applied to generate a degradation indicator on door systems since current signals of normal and abnormal behaviour have similar trends, except for the depth and width of fluctuations and negative peaks. Therefore, DTW distance is susceptible to those characteristics and can be a good representative of degradation. As a result, the DTW distance and K-means clustering algorithm can be used together for degradation estimation and fault severity assessment on railway door systems.

Certainly, one might argue that the explanation given in above is qualitative. However, this research does not utilise maintenance records. The way of fault severity assessment could be validated quantitatively with that information. Besides, the main contribution of the proposed method is a novel prognosis method without using RTF data, not a way of assessing faulty severity. Therefore, the K-means and the DTW are examples of fault severity assessment in the research, which means another method of fault severity assessment could be employed if that is more suitable.

B. THE REMAINING TIME PREDICTION

For the purpose of the remaining time prediction, ten severity stages are created by K-means instead of four stages, which is described and explained in Section IV-A. The ten stages in Section IV-B differ from the four levels used in Section IV-A. For the sake of clarity, the terminology stage is used in Section IV-B instead of the level to differentiate them. Certainly, it might be argued that ten stages of degradation are not well justified from an industrial point of view because it might be too many severity stages to be easily identified in practice. However, E. Balaban et al have presented an extensive analysis of the critical failure modes for EMAs and used ten stages as relative criticality [49]. Therefore, we used ten stages in order to predict the remaining time leading to critical fault severity level from each stage in this research. The critical fault severity is when a system has reached a point where maintenance cannot be delayed. The number of observations per week from stages 5 to 10 is described in Figure 10. Samples of stages 5, 6, and 7 are observable during the whole period, while those of stages 8, 9, and 10 cannot be detected before 3,653, 4,350, and 6,028 hours, respectively. Furthermore, the observation distribution looks to be moderately sliding from left to right over time through stages 5 to 10. If the time of each stage is determined with the median of observations belonging to each stage, the time of each stage is positively correlated with the stage numbers, as shown in Figure 11. If stage 10 is assumed to be critical fault severity level, the remaining time is estimated by subtracting the median time of each stage from that of stage 10, as shown in Figure 12. The result reveals that the remaining time can be predicted once the current severity

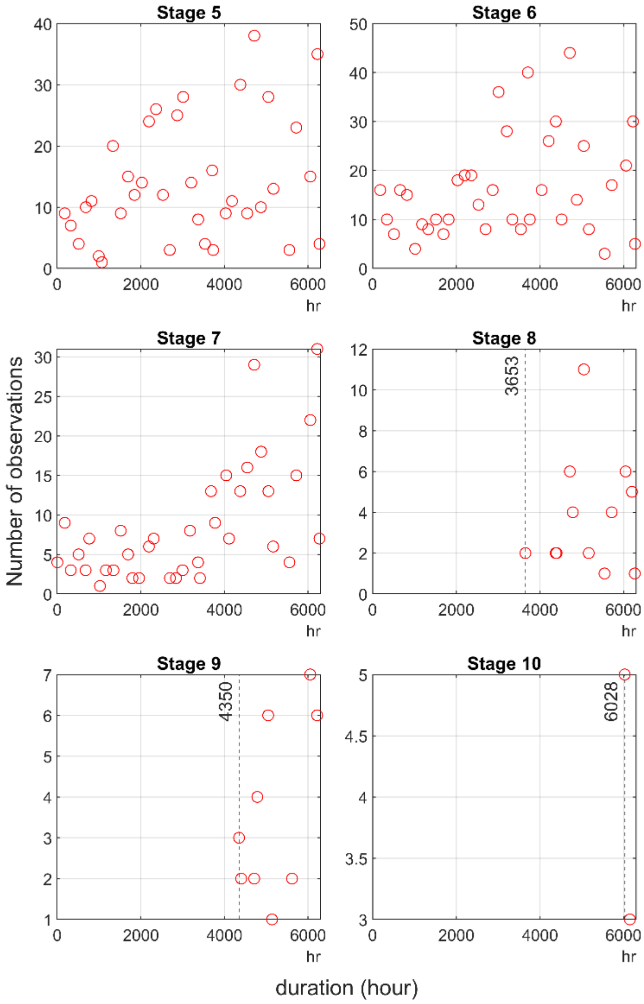

FIGURE 10. The number of observations from stages 5 to 10 per week.

stage can be assessed during operation. For instance, given that the current severity stage is considered stage 8, then the remaining time can be predicted as 995 hours.

Indeed, it might be argued the accuracy of the remaining time prediction needs to be verified. If maintenance records were available, the predicted remaining time could be validated quantitively, whose information is unavailable in this research. However, this research insists that data-driven prognosis methods have no validated input for end-of-life of individual assets in the real-world industry. Hence, the remaining useful life remains an estimate even though the gradient of the remaining time prediction is well monitored, as shown in Figure 12.

C. PREDICTIVE MAINTENANCE CAPABILITY

The proposed method could be a significant tool for real-world railway maintenance planning. The key idea is that the fault severity assessment and approximate remaining time prediction are often sufficient for decision making for maintenance planning. In this research, for instance, the ten stages can be classified into different alarm levels, which are normal (green), moderate (amber), severe (orange) and

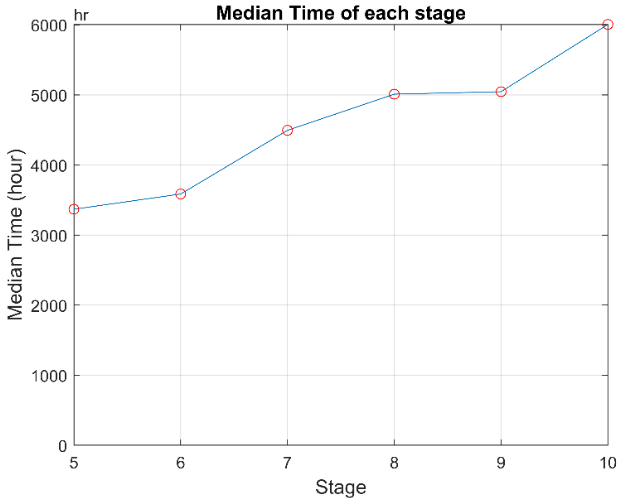

FIGURE 11. Median time of each stage.

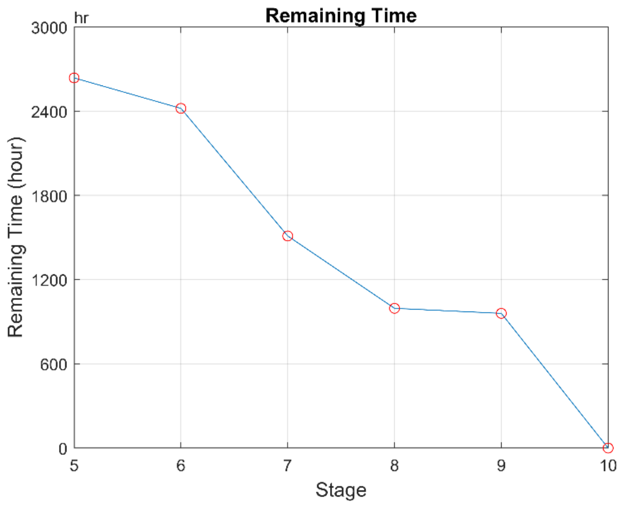

FIGURE 12. Remaining time prediction until stage 10.

Alarm Level	Normal				Moderate		Severe			Extreme
Stages	1	2	3	4	5	6	7	8	9	10
Remaining time (hours)	-	-	-	-	2637	2420	1511	995	959	0

FIGURE 13. Severity assessment level (Normal, Moderate, Severe and Extreme), stages and remaining time.

extreme (red) based on the predicted remaining time as described in Figure 13. Operations can be continued at the normal (green) alarm level without any maintenance. In the case of a moderate (amber) level, railway companies can still keep their operations going, but condition degradation indicators must be monitored carefully. They would need to start maintenance planning at the severe (orange) level, taking into account the remaining time before reaching an extreme (red) level because a certain amount of time would be required to plan maintenance. Maintenance can also be scheduled depending on a company's maintenance lead time and capability; for example, some companies need to schedule maintenance in stage 7 due to their maintenance ability. On the other hand, other companies might be able to conduct maintenance in stage 9 if they have enough resources. Once the alarm level reaches extreme (red), the assets need to be maintained immediately. Simply put, this means that maintenance can be scheduled and conducted with prognostic information before a catastrophic incident without using RTF data.

In addition, the fault severity threshold can be updated by using additional operational data, enabling the remaining time prediction to be more reliable. The fault severity threshold refers to the maximum fault severity stage. As an example, stage 10 can be assumed to be the fault severity threshold in Figure 13. The fault severity assessment model can be trained with the additional data, then, the model can generate more severity stages during operational data acquisition. This training enables the fault severity threshold to be updated and the remaining time prediction to be more reliable. In addition, the RUL can also be predicted using the proposed method once enough RTF data has been gathered during the operation.

Lastly, another advantage of the proposed method is that it can also 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. That is also beneficial for practical prognostic health management systems.

V. CONCLUSION

This novel prognosis method that does not require RTF data is an applicable and useful tool for real-world railway maintenance planning. The key idea is that fault severity assessments and approximate remaining time predictions are often all that is needed in order to plan maintenance. Therefore, this paper established a practical prognosis methodology that uses fault severity assessments and approximate remaining time predictions instead of RTF data to estimate accurate RUL.

Firstly, a degradation indicator on railway door systems is generated using motor current signals based on the DTW method to compare the behaviour of typical normal and faulty door systems. Then the K-means algorithm is applied to assess fault severity, followed by the time estimation of each fault severity level. To be concise, this estimation allows the remaining time until reaching the critical fault severity level to be predicted without using RTF data.

The proposed method offers significant advantages in terms of practical real-time prognostics and health management. Firstly, the proposed method can be applied to real-world railway maintenance planning as the remaining time can be predicted in real-time without using RTF data, which has previously been a great setback to building a prediction model. Secondly, the fault severity threshold can be updated by including additional operational data, enabling the remaining time prediction to be more reliable. The RUL can also be predicted using the proposed method once enough RTF data has been gathered during the operation. Additionally, the proposed method can also 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, which is also beneficial for practical prognostic health management systems.

Determining a confidence level in the prediction was out of this paper's scope, however future research into this would be fruitful. Next steps in this research journey could be to acquire operational data from different assets to generate a probability possibility density function in order to estimate a confidence level.

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REFERENCES

[1] N.-H. Kim, D. An, and J.-H. Choi, *Prognostics and Health Management Of Engineering Systems*. Cham, Switzerland: Springer, 2017, pp. 1–24, doi: 10.1007/978-3-319-44742-1_1.

[2] Y. Peng, M. Dong, and M. J. Zuo, "Current status of machine prognostics in condition-based maintenance: A review," *Int. J. Adv. Manuf. Technol.*, vol. 50, nos. 1–4, pp. 297–313, Jan. 2010, doi: 10.1007/S00170-009-2482-0.

[3] Health and Safety Executive. (Mar. 2003). *Train Derailment at Potters Bar—10 May 2002—A Progress Report by the HSE Investigation Board May 2003*. [Online]. Available: https://webarchive.nationalarchives.gov.uk/ukgwa/20081108234009/http%3A//www.rail-reg.gov.uk/upload/pdf/incident-pottersbar-may03progrep.pdf

[4] G. Vachtsevanos, F. Lewis, M. Roemer, A. Hess, and B. Wu, "Fault Prognosis," in *Intelligent Fault Diagnosis and Prognosis for Engineering Systems*, Hoboken, NJ, USA: Wiley, 2007, pp. 284–354, doi: 10.1002/9780470117842.ch6.

[5] O. F. Eker, F. Camci, and I. K. Jennions, "A new hybrid prognostic methodology," *Int. J. Prognostics Health Manag.*, vol. 10, no. 2, Jun. 2019, doi: 10.36001/ijphm.2019.v10i2.2727.

[6] L. Liao and F. Köttig, "Review of hybrid prognostics approaches for remaining useful life prediction of engineered systems, and an application to battery life prediction," *IEEE Trans. Rel.*, vol. 63, no. 1, pp. 191–207, Mar. 2014, doi: 10.1109/TR.2014.2299152.

[7] E. Zio and G. Peloni, "Particle filtering prognostic estimation of the remaining useful life of nonlinear components," *Reliab. Eng. Syst. Saf.*, vol. 96, no. 3, pp. 403–409, 2011, doi: 10.1016/J.RESS.2010.08.009.

[8] D. An, J.-H. Choi, and N. H. Kim, "Prognostics 101: A tutorial for particle filter-based prognostics algorithm using MATLAB," *Rel. Eng. Syst. Saf.*, vol. 115, pp. 161–169, Jul. 2013, doi: 10.1016/J.RESS.2013.02.019.

[9] M. J. Daigle and K. Goebel, "Model-based prognostics with concurrent damage progression processes," *IEEE Trans. Syst., Man, Cybern., Syst.*, vol. 43, no. 3, pp. 535–546, May 2013, doi: 10.1109/TSMCA.2012.2207109.

[10] S. Butler and J. Ringwood, "Particle filters for remaining useful life estimation of abatement equipment used in semiconductor manufacturing," in *Proc. Conf. Control Fault-Tolerant Syst. (SysTol)*, Oct. 2010, pp. 436–441, doi: 10.1109/SYSTOL.2010.5675984.

[11] M. Daigle and K. Goebel, "Model-based prognostics under limited sensing," in *Proc. IEEE Aerosp. Conf.*, Mar. 2010, pp. 1–12, doi: 10.1109/AERO.2010.5446822.

[12] M. Samie, S. Perinpanayagam, A. Alghassi, A. M. S. Motlagh, and E. Kapetanios, "Developing prognostic models using duality principles for DC-to-DC converters," *IEEE Trans. Power Electron.*, vol. 30, no. 5, pp. 2872–2884, May 2015, doi: 10.1109/TPEL.2014.2376413.

[13] X.-S. Si, W. Wang, C.-H. Hu, and D.-H. Zhou, "Remaining useful life estimation—A review on the statistical data driven approaches," *Eur. J. Oper. Res.*, vol. 213, no. 1, pp. 1–14, Aug. 2011, doi: 10.1016/J.EJOR.2010.11.018.

[14] P. Wang and G. Vachtsevanos, "Fault prognostics using dynamic wavelet neural networks," *Artif. Intell. Eng. Des., Anal. Manuf.*, vol. 15, no. 4, pp. 349–365, Sep. 2001, doi: 10.1017/S0890060401154089.

[15] K. Pugalenthi, H. Park, S. Hussain, and N. Raghavan, "Hybrid particle filter trained neural network for prognosis of lithium-ion batteries," *IEEE Access*, vol. 9, pp. 135132–135143, 2021, doi: 10.1109/ACCESS.2021.3116264.

[16] J. Yan, M. Koç, and J. Lee, "A prognostic algorithm for machine performance assessment and its application," *Prod. Planning Control*, vol. 15, no. 8, pp. 796–801, Dec. 2004, doi: 10.1080/09537280412331309208.

[17] M. Xia, T. Li, T. Shu, J. Wan, C. W. de Silva, and Z. Wang, "A two-stage approach for the remaining useful life prediction of bearings using deep neural networks," *IEEE Trans. Ind. Informat.*, vol. 15, no. 6, pp. 3703–3711, Jun. 2019, doi: 10.1109/TII.2018.2868687.

[18] A. Al-Dulaimi, S. Zabihi, A. Asif, and A. Mohammadi, "Hybrid deep neural network model for remaining useful life estimation," in *Proc. IEEE Int. Conf. Acoust., Speech Signal Process. (ICASSP)*, May 2019, pp. 3872–3876, doi: 10.1109/ICASSP.2019.8683763.

[19] L. Ren, Y. Sun, J. Cui, and L. Zhang, "Bearing remaining useful life prediction based on deep autoencoder and deep neural networks," *J. Manuf. Syst.*, vol. 48, pp. 71–77, Jul. 2018, doi: 10.1016/j.jmsy.2018.04.008.

[20] J. Ma, H. Su, W.-L. Zhao, and B. Liu, "Predicting the remaining useful life of an aircraft engine using a stacked sparse autoencoder with multilayer self-learning," *Complexity*, vol. 2018, pp. 1–13, Jul. 2018, doi: 10.1155/2018/3813029.

[21] C. Zhang, P. Lim, A. K. Qin, and K. C. Tan, "Multiobjective deep belief networks ensemble for remaining useful life estimation in prognostics," *IEEE Trans. Neural Netw. Learn. Syst.*, vol. 28, no. 10, pp. 2306–2318, Oct. 2017, doi: 10.1109/TNNLS.2016.2582798.

[22] Y. T. Wu, M. Yuan, S. Dong, L. Li, and Y. Liu, "Remaining useful life estimation of engineered systems using vanilla LSTM neural networks," *Neurocomputing*, vol. 275, pp. 167–179, Jan. 2018, doi: 10.1016/J.NEUCOM.2017.05.063.

[23] R. Kizito, P. Scruggs, X. Li, M. Devinney, J. Jansen, and R. Kress, "Long short-term memory networks for facility infrastructure failure and remaining useful life prediction," *IEEE Access*, vol. 9, pp. 67585–67594, 2021, doi: 10.1109/ACCESS.2021.3077192.

[24] L. Zhang and J. Zhang, "A data-driven maintenance framework under imperfect inspections for deteriorating systems using multitask learning-based status prognostics," *IEEE Access*, vol. 9, pp. 3616–3629, 2021, doi: 10.1109/ACCESS.2020.3047928.

[25] G. Hou, S. Xu, N. Zhou, L. Yang, and Q. Fu, "Remaining useful life estimation using deep convolutional generative adversarial networks based on an autoencoder scheme," *Comput. Intell. Neurosci.*, vol. 2020, pp. 1–14, Aug. 2020, doi: 10.1155/2020/9601389.

[26] D. Zhen, T. Wang, F. Gu, and A. D. Ball, "Fault diagnosis of motor drives using stator current signal analysis based on dynamic time warping," *Mech. Syst. Signal Process.*, vol. 34, nos. 1–2, pp. 191–202, Jan. 2013, doi: 10.1016/J.YMSSP.2012.07.018.

[27] C. T. Yiakopoulos, K. C. Gryllias, and I. A. Antoniadis, "Rolling element bearing fault detection in industrial environments based on a K-means clustering approach," *Exp. Syst. Appl.*, vol. 38, no. 3, pp. 2888–2911, Mar. 2011, doi: 10.1016/J.ESWA.2010.08.083.

[28] S. Kim, N. H. Kim, and J.-H. Choi, "Prediction of remaining useful life by data augmentation technique based on dynamic time warping," *Mech. Syst. Signal Process.*, vol. 136, Feb. 2020, Art. no. 106486, doi: 10.1016/J.YMSSP.2019.106486.

[29] Z. Tian, L. Wong, and N. Safaei, "A neural network approach for remaining useful life prediction utilizing both failure and suspension histories," *Mech. Syst. Signal Process.*, vol. 24, no. 5, pp. 1542–1555, Jul. 2010, doi: 10.1016/j.ymssp.2009.11.005.

[30] C. Hu, B. D. Youn, T. Kim, and P. Wang, "A co-training-based approach for prediction of remaining useful life utilizing both failure and suspension data," *Mech. Syst. Signal Process.*, vols. 62–63, pp. 75–90, Oct. 2015, doi: 10.1016/j.ymssp.2015.03.004.

[31] D. An, J.-H. Choi, and N. H. Kim, "Prediction of remaining useful life under different conditions using accelerated life testing data," *J. Mech. Sci. Technol.*, vol. 32, no. 6, pp. 2497–2507, Jun. 2018, doi: 10.1007/s12206-018-0507-z.

[32] A. De Martin, G. Jacazio, and G. Vachtsevanos, "Windings fault detection and prognosis in electro-mechanical flight control actuators operating in active-active configuration," *Int. J. Prognostics Health Manag.*, vol. 8, no. 2, p. 17, Nov. 2020, doi: 10.36001/IJPHM.2017.V8I2.2633.

[33] C. S. Byington, M. Watson, and D. Edwards, "Data-driven neural network methodology to remaining life predictions for aircraft actuator components," in *Proc. IEEE Aerosp. Conf.*, Mar. 2004, pp. 3581–3589, doi: 10.1109/AERO.2004.1368175.

[34] E. Balaban, A. Saxena, S. Narasimhan, I. Roychoudhury, and K. Goebel, ''Experimental validation of a prognostic health management system for electro-mechanical actuators,'' in *Proc. Infotech@Aerospace*, Mar. 2011, p. 1518, doi: 10.2514/6.2011-1518.

[35] E. Balaban, A. Saxena, S. Narasimhan, I. Roychoudhury, M. Koopmans, C. Ott, and K. Goebe, ''Prognostic health-management system development for electromechanical actuators,'' *J. Aerosp. Inf. Syst.*, vol. 12, no. 3, pp. 329–344, Mar. 2015, doi: 10.2514/1.I010171.

[36] Y. Zhang, D. Liu, J. Yu, Y. Peng, and X. Peng, ''EMA remaining useful life prediction with weighted bagging GPR algorithm,'' *Microelectron. Rel.*, vol. 75, pp. 253–263, Aug. 2017, doi: 10.1016/j.microrel.2017.03.021.

[37] P. C. C. Berri, M. D. L. D. Vedova, and L. Mainini, ''Real-time fault detection and prognostics for aircraft actuation systems,'' in *Proc. AIAA Scitech Forum*, Jan. 2019, p. 2210, doi: 10.2514/6.2019-2210.

[38] P. C. Berri, M. D. L. D. Vedova, and L. Mainini, ''Computational framework for real-time diagnostics and prognostics of aircraft actuation systems,'' *Comput. Ind.*, vol. 132, Nov. 2021, Art. no. 103523, doi: 10.1016/J.COMPIND.2021.103523.

[39] A. Caliwag, S.-Y. Han, K.-J. Park, and W. Lim, ''Deep-learning-based fault occurrence prediction of public trains in South Korea,'' *Transp. Res. Rec., J. Transp. Res. Board*, vol. 2676, no. 4, pp. 710–718, Feb. 2022, doi: 10.1177/03611981211064893.

[40] M. Shimizu, S. Perinpanayagam, and B. Namoano, ''Real-time techniques for fault detection on railway door systems,'' in *Proc. IEEE Aerosp. Conf.*, Aug. 2022, pp. 1-9, doi: 10.1109/AERO53065.2022.9843627.

[41] B. Namoano, ''Fault diagnosis in time series data with application to railway assets,'' Ph.D. Thesis, School Aerosp., Transp. Manuf., Eng. Manag. Manuf. Syst., Cranfield Univ., Cranfield, U.K., 2020.

[42] C. S. Myers and L. R. Rabiner, ''A comparative study of several dynamic time-warping algorithms for connected-word recognition,'' *Bell Syst. Tech. J.*, vol. 60, no. 7, pp. 1389–1409, 1981, doi: 10.1002/j.1538-7305.1981.tb00272.x.

[43] H. Sakoe and S. Chiba, ''Dynamic programming algorithm optimization for spoken word recognition,'' *IEEE Trans. Acoust., Speech, Signal Process.*, vol. ASSP-26, no. 1, pp. 43–49, Feb. 1978, doi: 10.1109/TASSP.1978.1163055.

[44] M. Muller, ''Dynamic time warping,'' in *Information Retrieval for Music and Motion*. Berlin, Germany: Springer, 2007, pp. 69–84, doi: 10.1007/978-3-540-74048-3_4.

[45] D. Dinler and M. K. Tural, ''A survey of constrained clustering,'' in *Unsupervised Learning Algorithms*. Cham, Switzerland: Springer, 2016, pp. 207–235, doi: 10.1007/978-3-319-24211-8_9.

[46] S. Ham, S.-Y. Han, S. Kim, H. J. Park, K.-J. Park, and J.-H. Choi, ''A comparative study of fault diagnosis for train door system: Traditional versus deep learning approaches,'' *Sensors*, vol. 19, no. 23, p. 5160, Nov. 2019, doi: 10.3390/s19235160.

[47] A. Glowacz and Z. Glowacz, ''Diagnosis of stator faults of the single-phase induction motor using acoustic signals,'' *Appl. Acoust.*, vol. 117, pp. 20–27, Feb. 2017, doi: 10.1016/j.apacoust.2016.10.012.

[48] D. Arthur and S. Vassilvitskii, ''K-means++: The advantages of careful seeding,'' in *Proc. 18th Annu. ACM-SIAM Symp. Discrete Algorithms (SODA)*, New Orleans, LA, USA, Jan. 2007, pp. 1027–1035.

[49] E. Balaban, P. Bansal, P. Stoelting, A. Saxena, K. F. Goebel, and S. Curran, ''A diagnostic approach for electro-mechanical actuators in aerospace systems,'' in *Proc. IEEE Aerosp. Conf.*, Mar. 2009, pp. 1–13, doi: 10.1109/AERO.2009.4839661.

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