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Degradation-level Assessment and Online Prognostics for Sliding Chair Failure on Point Machines

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Abstract: This paper presents a degradation-level assessment and failure prognostics methodology for degrading systems. The proposed methodology consists of offline and online phases. In the offline phase, different time-domain health indicators (HIs) are extracted and the best indicator of degradation is selected by filter-based methods. Then, a degradation model is defined and its parameters are estimated using the selected HI. In the online phase, the k-means clustering is utilized to detect a change(s) in the system's health state and to trigger failure prognostics for remaining useful life (RUL) prediction. The degradation model parameters are updated as new data are available, and the RUL is predicted iteratively. The proposed methodology is implemented on point machine sliding chair degradation using *in-field* condition monitoring (CM) data. The results show that the methodology can be effectively used in machine degradation-level assessment and in online RUL predictions.

Keywords: degradation-level assessment, clustering, change-point detection, failure prognostics, RUL prediction, railway point machines, sliding-chair degradation, predictive maintenance.

1. INTRODUCTION

Machine degradation-level assessment (MDA) is one of the important issues in Prognostics and Health management (PHM) discipline. The MDA analyses the machine failure propagation to get knowledge about the hidden health state transitions either from raw data (e.g. batteries) or from constructed health indicators (HIs), before triggering prognostics tools. Hence, the MDA information can be used in the development of robust prognostics models in incipient failure detection to trigger remaining-useful-life (RUL) prediction for complex systems (e.g. railway point machines, high-speed train bogies, wind turbines, nuclear power plants and aircrafts (X. Wang et al. 2016)).

Railway turnout systems, which consist of sliding-chair plates, point machine, stock rails, locking systems, etc., are used to manage the train turnouts by moving rail blades at a distance. Hence, the point machine health assessment is very crucial to increase operational reliability and passenger safety in railway transportation. In general, there are different types of point machines, such as hydraulic, electro-mechanical and pneumatic (Atamuradov et al. 2009). In (Z. Wang et al. 2016), the authors proposed an integrated feature extraction methodology based on singular value decomposition (SVD) and empirical mode decomposition (EMD) techniques and the Mahalanobis distance metric for fault detection of electro-mechanical point machines using power signals acquired from the point machine test bench. A similar work was also

conducted in (Yoon et al. 2016) using *in-field* DC current signals based on Dynamic Time Warping (DTW) technique for point machine fault detection. In (Jin et al. 2015), the authors proposed a systematic health assessment methodology for point machine fault diagnostics using simulated failure modes' data. The power signal was divided into 7 segments using the motor speed parameters and statistical features were extracted from each segment for further analysis. By using self-organizing maps (SOM) and principal component analysis (PCA) techniques, the authors successfully evaluated the methodology in point machine degradation-level assessment and incipient fault detection. In (Asada et al. 2013), the authors proposed a fault diagnostics methodology using Discrete-Wavelets Decomposition (DWT) and Support Vector Machine (SVM) classifier for electro-mechanical point machines. The DWT was employed in feature extraction and reduction steps before SVM based fault classification. The k-means clustering was utilized to select the best DWT type and decomposition level in feature selection and reduction step. Afterward, different failure modes were efficiently classified by kernel-based SVM classifier using DWT based features. In (Eker et al. 2011; Eker & Camci 2013), the authors presented a state duration based methodology for point machine failure prognostics. The point machine degradation was modeled artificially using an exponential failure propagation function. The proposed methodology gave better RUL prediction results when compared to different prognostics tools. A data-driven failure prognostics model was proposed in (Letot et al. 2015) for point machine health assessment using the power signals

acquired from the test bench. The point machine degradation model, which is the combination of linear and exponential functions, was built using an extracted time-domain based HI to predict the RUL of the system. A generic fault detection methodology was presented in (Atamuradov et al. 2017) based on a segment evaluation and inferential statistics approach. The authors extracted different statistical HIs from the DC current signal of point machine and employed data fusion to construct a unique system HI. The fused HI was further used in fault detection by segment evaluation. In (Ashasi-Sorkhabi et al. 2017), the authors proposed fault detection and prognostics approach for automated people mover train gearbox. The fault detection was carried out online using an extracted HIs from vibration signals and the data-driven prognostics model parameters were updated based on a Bayesian approach and was validated on the periodically logged field data. Air leakage detection and failure prediction approach for the train braking system was proposed in (Lee 2017). A regression classifiers were used in failure modes modeling and a density-based clustering was utilized to detect the leakage anomalies using compressor data. The methodology was efficiently demonstrated in anomaly detection and severity prediction based on logistic function. Several interesting types of research on point machine fault diagnostics can also be found in (García Márquez et al. 2010; García Márquez et al. 2007) papers. Moreover, failure prognostics approaches which were proposed for discrete systems can be found in (Ammour et al. 2017; Yin 2017).

As been summarized in the previous paragraph, the point machine health assessment is an important task to increase reliability and safety in railway transportation and very challenging. This could be due to the insufficient data, unavailable failure modes which develop in long-period of time (Eker et al. 2011) and nonlinear system degradation behavior that makes constructing trendable system HIs hard, if not impossible. The sliding chair plates of the point machine can experience different degradation states (i.e. healthy, moderate and severe states) throughout their lifespan before the complete failure. To forecast the future degradation behavior of the sliding chair plates, it is important to detect a change-point(s) that the machine falls into a faulty state from healthy state. In practice, it is important to note that there can be more than one changing point (see Fig. 1) due to some physical phenomena. In this case, each degradation level ($D_{1,2,3,4}$ in Fig. 1) should be evaluated (i.e. testing the failure severity criteria) differently, and the prognostics should be triggered when the machine switches to a severe health state.

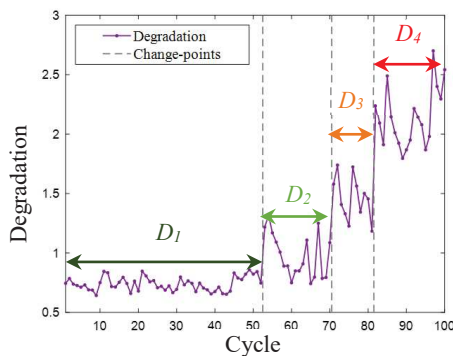


Fig. 1. Machine health state changes.

Therefore, a machine degradation-levels should be properly assessed to detect an incipient fault before triggering a prognostics algorithm. This paper presents a MDA and failure prognostics methodology for point machine sliding chair degradation. In the offline phase of the proposed methodology, different statistical HIs are extracted from *in-field* condition monitoring (CM) data and selected by filter based HI selection, utilizing monotonicity and similarity statistics. Then, a double exponential degradation model is built and the parameters are estimated using the selected HI. In the online phase, an unsupervised technique, which is k-means, is used to detect the changing point(s) by grouping newly received HI data, before the prognostics. Finally, the prognostics model is triggered to predict the RUL. As new data points are available, the model parameters are re-estimated and the component RUL is predicted iteratively. The main contributions of this work, compared to the reviewed papers are 1) HI selection by two step intraclass and interclass feature analysis using filter methods, 2) unsupervised change-point detection and 3) RUL prediction based on online prognostics model update by windowing approach.

The paper is organized as follows: Section 2 explains the proposed methodology steps. Section 3 presents the sliding chair degradation modeling and the experimental rig setup. The results are presented in Section 4. Section 5 concludes the paper.

2. METHODOLOGY

The proposed methodology consists of offline and online phases. In the offline phase, the health indicator construction and the degradation model definition is presented. The online phase includes the clustering based change-point detection and the RUL prediction steps. The general scheme of the proposed methodology is depicted in Fig. 2.

2.1 Health Indicator Extraction and Selection

A HI extraction can be defined as an extraction of useful and important hidden information from raw data that indicates health state transitions in a system degradation. In this paper, time-domain based HIs such as *root-mean-square (rms)*, *kurtosis*, *skewness*, *crest factor (crfactor)*, *standard deviation (stdev)* and *peak-to-peak (p2p)* are extracted. The HI selection is carried out in two steps. The HIs which have a higher monotonicity value than the calculated sample mean are selected first in step 1 (intraclass analysis). In step 2 (interclass analysis), a similarity matrix is constructed from the selected HIs using the Euclidean distance. The best HI is then selected from the similarity matrix mean which has a minimum distance value. In the intraclass selection, the most trendable HIs are selected and in the interclass selection, the most representative HI is selected among the trendable HIs. The monotonicity is calculated using equation (1) and the Euclidean distance is calculated using equation (2). The similarity matrix ($simM$) is constructed as indicated in equation (3). The most representative HI is selected by using equation (4).

$$M_i = \left(\frac{\# \frac{d}{dHI_i} > 0}{n-1} - \frac{\# \frac{d}{dHI_i} < 0}{n-1} \right) \quad (1)$$

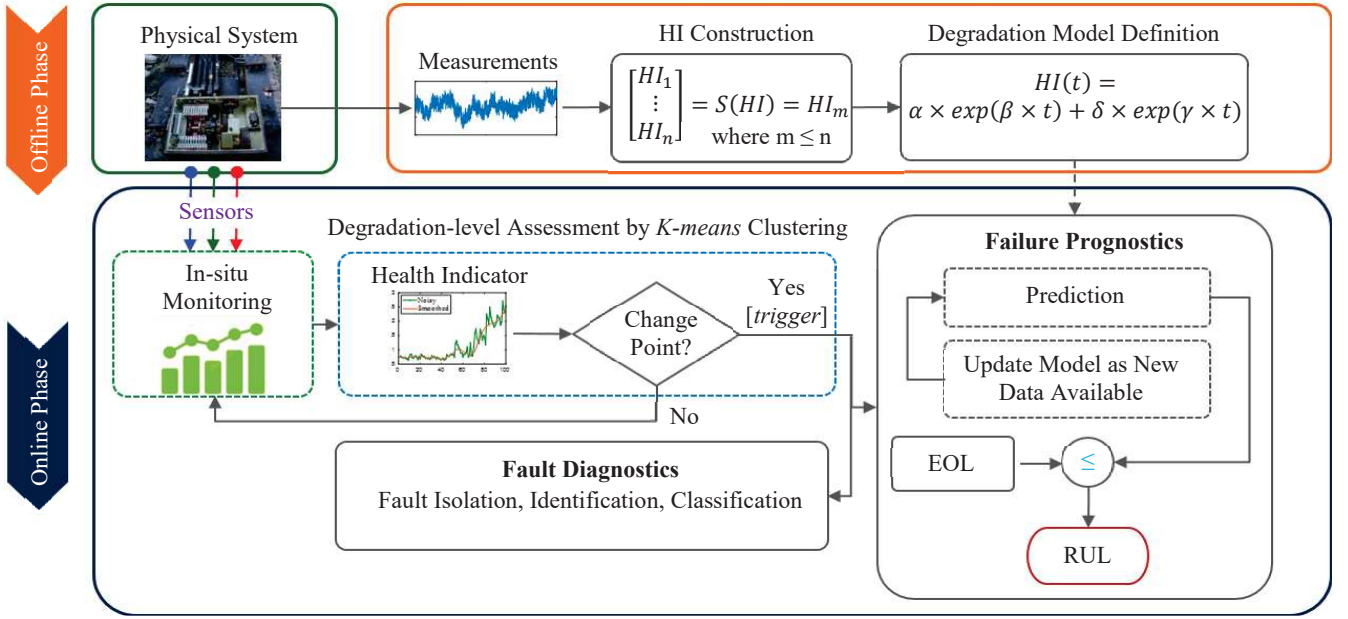


Fig. 2. Two-step degradation-level assessment and failure prognostics methodology scheme.

where M_i is the monotonicity value for the i^{th} HI (HI_i). The absolute value of the difference between number of positive ($\# \frac{d}{dHI_i} > 0$) and negative derivatives ($\# \frac{d}{dHI_i} < 0$) gives the monotonicity value. A HI with the higher monotonicity indicates the better degradation with an increasing/decreasing trend.

$$dist(p, q) = \sqrt{\sum_{i=1}^N (p_i - q_i)^2} \quad (2)$$

where N is the length of the given HIs p and q .

$$simM = \begin{bmatrix} dist(h_1h_1) & \cdots & dist(h_1h_M) \\ \vdots & \ddots & \vdots \\ dist(h_Mh_1) & \cdots & dist(h_Mh_M) \end{bmatrix}_{M \times M} \quad (3)$$

$$bestHI = \min(\mu(simM)) \quad (4)$$

where $dist(h_1h_M)$ is the distance value between the health indicators h_1 and h_M from the data pool with size M and μ is the similarity mean value.

2.2 Clustering based Degradation-level Assessment

A *k-means* (Lloyd 1982) unsupervised machine learning technique is adopted in this paper in MDA for change-point(s) detection.

The *k-means* groups a given X dataset ($X = x_1, x_2 \dots x_n$) into C ($C = C_1, C \dots C_k$) clusters. The similarity degree between the cluster center μ_i and the data points is based on an Euclidean distance, where $i = 1, 2, \dots C$. The goal is to minimize the objective function expressed by:

$$J(\mu, u) = \sum_{j=1}^n \sum_{k=1}^C u_{k,j} \|x_j - \mu_k\|^2 \quad (5)$$

where $u_{k,j} \in \{0,1\}$ is the membership value of the data point x_j to the cluster C_k . The best partition number can be identified by using cluster validity techniques (Maulik & Bandyopadhyay 2002). In this paper, well-known within cluster consistency evaluation technique, which is Silhouette

(Rousseeuw 1987) evaluation, is adopted for cluster validation.

2.3 Degradation Model for Failure Prognostics

First, the degradation trend of the selected HI is extracted by using a moving average noise filtration technique before the curve fitting step. In this research, a double exponential function, which was proposed in (Skima et al. 2016), is adopted in the sliding chair degradation modeling due to its good degradation representability as given in (6).

$$f(t)_{HI} = \alpha \times \exp(\beta \times t) + \delta \times \exp(\gamma \times t) \quad (6)$$

where $f(t)_{HI}$ is the model output at time t and $\alpha, \beta, \delta, \gamma$ are the model parameters. The degradation model parameters are estimated in the offline phase. In the online phase, after the detection of changing point, failure prognostics is triggered to predict the RUL of the sliding chairs. As new data values are available, the model parameters are re-estimated and the system RUL is predicted iteratively until the end-of-life (EOL) threshold is reached. To update the exponential model parameters in the online phase, it is obligatory to have sufficient amount of data points. In this study, the model update is performed after each 5 and 10 time stamps. The RUL prediction accuracy (P_{Acc}) is calculated by using equation (7) (Tobon-Mejia et al. 2012).

$$P_{Acc} = \frac{1}{B} \sum_{b=1}^B -\exp |RUL_r(b) - RUL_e(b)| / RUL_p(b) \quad (7)$$

where B is the number of data point used in RUL prediction. For the best prediction performance, the P_{Acc} produces 1 and 0 for the worst.

3. EXPERIMENTAL SETUP AND DATA COLLECTION

Since the point machines are highly reliable systems, the degradation of their components can take a long period of time (Gebrael, Elwany, & Pan 2009), which makes failure prognostics very hard. To overcome this problem, the sliding

chair degradation is simulated by an accelerated aging procedure on the real system. The sliding chair plates support the point machines to move the rail blades from normal-to-reverse and reverse-to-normal positions. There were totally 12 lubricated (i.e. healthy) sliding chair plates on the turnout system. The first sliding chair failure state was generated by contaminating the farthest 10th, 11th and 12th plates. The second faulty state was acquired by contaminating the 9th farthest plate. By adding a new contaminated plate to the faulty group, we generated a complete point machine sliding chair failure. There are totally 10 different health states (10 samples/health state) which were generated by the accelerated aging. The resistive force sensory data has been investigated in this research due to good degradation representation property (Camci et al. 2016; Ardakani et al. 2012). An electro-mechanical point machine, an installed force sensor and the sliding chair plates which were investigated in this current research, are depicted in Fig. 3. The real turnout system and the sliding chair degradation modeling are shown in Fig. 4. The resistive force time series and one sample from each healthy and faulty states of the sliding chair degradation are depicted in Fig. 5.

4. RESULTS AND DISCUSSIONS

The point machine resistive force measurements went through HI extraction step to reveal the sliding chair plate degradation patterns. Before calculating the monotonicity values, the extracted HIs should be smoothed. The extracted and smoothed HIs by using Moving Average are shown in Fig. 6. As depicted in Fig. 6, the extracted descriptive statistics gave different degradation patterns, where some of them are not correlated with the sliding chair degradation. The extracted HIs went through two- steps: intraclass and interclass HI selection to select the best HI representing the sliding chair failure propagation, as it was explained in section 2. The calculated monotonicity values of the given HIs are shown in Fig. 7. The *rms*, *stdev* and *p2p* have been selected as the most trendable indicators from the intraclass selection, and fed into the interclass selection for the best HI selection. Before building the similarity matrix (equation (3)), the selected HIs

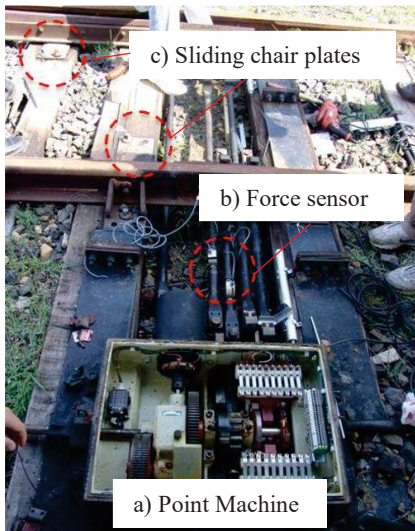


Fig. 3. a) Point machine b) installed force sensor and c) sliding chair plates.

were normalized between [0,1]. The calculated interclass similarity values for the given HIs are presented in Table 1. Based on the proposed filter health indicator selection method,

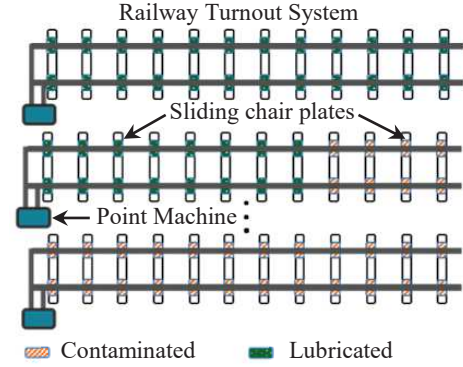


Fig. 4. Turnout system and sliding-chair degradation simulation.

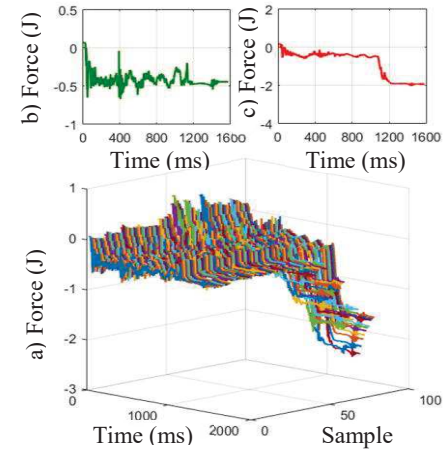


Fig. 5. a) Force time series and b) healthy, c) faulty data samples for sliding chair degradation.

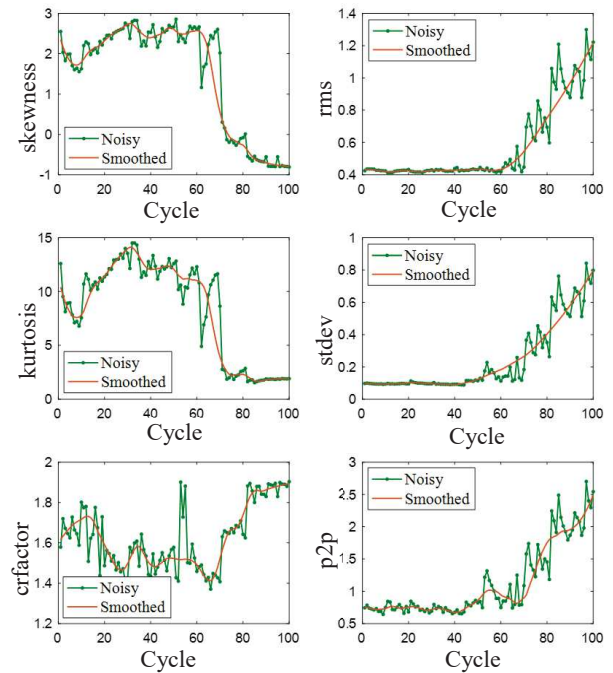


Fig. 6. Extracted HIs from force measurements.

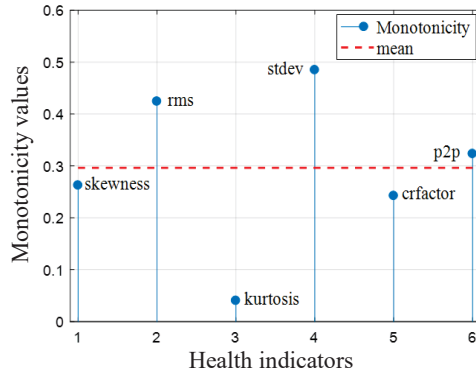


Fig. 7. Calculated monotonicity values for a given HIs.

Table 1. Similarity matrix for selected HIs.

	rms	stdev	p2p
rms	0	0.34	0.75
stdev	0.34	0	0.50
p2p	0.75	0.50	0
Average	0.54	0.42	0.62

stdev has been selected as the best representative and the most supported HI with minimum distance for the sliding chair degradation. It is also important to note that the selected *stdev* has the highest monotonicity value (see Fig. 7) compared to the others, which proves the efficiency of the proposed filter method for failure prognostics. The proposed exponential degradation model was fitted to *stdev* to estimate the model parameters in the offline phase. The estimated degradation model parameters obtained by curve fitting and the goodness of fit (R^2) are given in Table 2.

After the degradation model definition in the offline step, the selected HI went through the k-means based change-point detection to trigger failure prognostics for RUL prediction in the online phase. The cluster number was optimized by using Silhouette validation. The maximum Silhouette value refers to the best cluster number. The k-means has efficiently clustered the given HI into two degradation-levels. The change-point detection result is depicted in Fig. 8. The first level corresponds to the healthy state and the second level to the failure state. The last index (cycle # 71) of the 1st degradation-level is the changing point in the sliding chair degradation, which indicates the incipient failure. The change-point is used to launch the RUL prediction. The RUL prediction results are shown in Fig. 9. After the first trigger, the model parameters are not updated until the new data values are available. In this study, the waiting time was performed using two different window sizes. The purpose was to check the accuracy of the prognostics model with a given amount of data and to optimize the RUL prediction interval for better maintenance planning in machine condition monitoring. The RUL prediction results using window length 5 (W-5) and 10 (W-10) for the model update is given in Fig. 10. As seen from Fig. 10, the W-10 converged to the real RUL faster than the W-5 in its first update process. But using a longer window size can be a disadvantage and can affect maintenance planning negatively, especially for critical components such as sliding chairs. Despite its computational complexity, the W-5 based model updating is more precise than the W-10. The RUL prediction performances for W-5 and for W-10 were calculated as 0.90

and 0.81 using the equation (7). Hence, using a shorter window size in model updating could be more efficient for RUL prediction of critical systems to be used in post-prognostics decision making.

Table 2. Estimated degradation model parameters.

Parameters	a	b	c	d	R^2
Values	0.097	-0.038	0.018	0.038	0.99

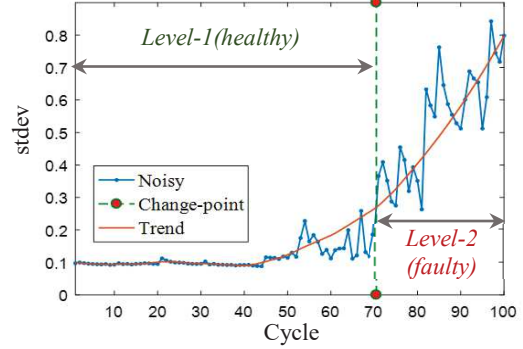


Fig. 8. Change-point detection results using k-means.

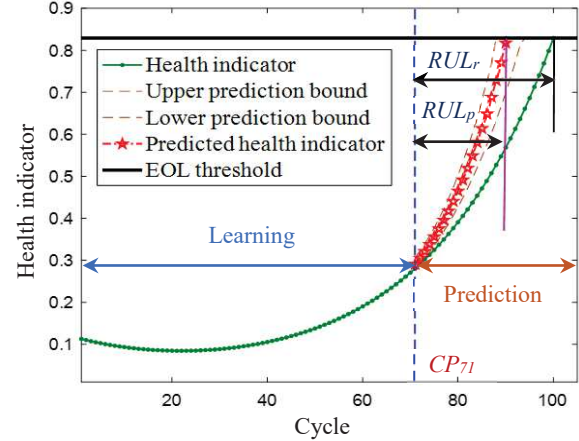


Fig. 9. RUL prediction (RUL_r – real and RUL_p – predicted) after the change-point detection (CP_{71}).

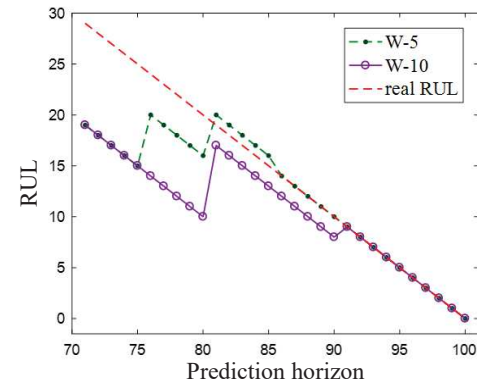


Fig. 10. RUL prediction results using window sizes a) five (W-5) and b) ten (W-10).

5. CONCLUSIONS

In this paper, a degradation-level assessment and an online prognostics approach were proposed for a point machine sliding chair monitoring. The two-step filter method was proposed for HI extraction and selection. A degradation-level

assessment based on the k-means was performed to detect change(s) in the component health state transitions. The k-means could only detect the bigger change in the health state but was less sensitive to smaller changes in failure propagation, which might mislead to late RUL predictions. The data-driven based prognostics model was developed and the RUL of the system was predicted using two different time stamps and the results were compared.

As a future work, we plan to utilize different change-point detection algorithms which are more sensitive to smaller changes and to develop prognostics approach based on failure severity criteria for systems experiencing different health state transitions (i.e. healthy, moderate, severe, etc.).

6. ACKNOWLEDGEMENTS

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