Fault Detection By Segment Evaluation Based On Inferential Statistics For Asset Monitoring

Vepa Atamuradov[1], Kamal Medjaher[1], Benjamin Lamoureux[2], Pierre Dersin[2] and Noureddine Zerhouni[3]

[1]*Production Engineering Laboratory (LGP), INP-ENIT 47 Av. d'Azereix, 65000 Tarbes, France*
vepa.atamuradov@enit.fr
kamal.medjaher@enit.fr

[2]*ALSTOM Transport, 93400 Saint-Ouen, France*
pierre.dersin@transport.alstom.com
benjamin.lamoureux@transport.alstom.com

[3]*FEMTO-ST Institute, UMR CNRS 6174 – UFC/ENSMM 15B av. des Montboucons, 25000 Besançon, France*
zerhouni@ens2m.fr

ABSTRACT

Detection of unexpected events (e.g. anomalies and faults) from monitoring data is very challenging in machine health assessment. Hence, abrupt or incipient fault detection from the monitoring data is very crucial to increase asset safety, availability and reliability. This paper presents a generic methodology for abrupt and incipient fault detection and feature fusion for health assessment of complex systems. Proposed methodology consists of feature extraction, feature fusion, segmentation and fault detection steps. First of all, different features are extracted using descriptive statistics. Secondly, based on linearly weighted data fusion algorithm, extracted features are combined to get the generic and representative feature. Afterward, combined feature is divided into homogeneous segments by sliding window segmentation algorithm. Finally, each segment is further evaluated by coefficient of variability which is used in inferential statistics, to evaluate health state changes that indicate asset faults. To illustrate its effectiveness, the methodology is implemented on point machine and Li-ion battery monitoring data to detect abrupt and incipient faults. The results show that proposed methodology can be effectively used in fault detection for asset monitoring.

1. INTRODUCTION

System performance degradation can be expressed as a combination of changes in health state transitions that can lead the system to complete failure. Diagnostics, which is one of the important tasks of Prognostics and Health Management (PHM) discipline, is defined as a determination of faults' or failures' nature by examining observed symptoms from the condition monitoring (CM) data (ISO 13372:2012 n.d.). Diagnostics enables to detect faults, isolate and identify failure modes from the CM data by means of classification and clustering tools. One of the challenging steps in asset diagnostics is how to detect faults by assessing a system health state transitions (e.g. from healthy to faulty) that can change while system degrades. Fault (e.g. incipient or abrupt) detection is known as anomaly detection in system behavior by analyzing the CM data.

Wu et al. (2015) proposed a fault information residual estimation methodology to detect incipient faults in high-speed train suspension system. Authors validated their fault detection methodology on simulated faulty signals. A bearing diagnostics was studied in (Pennacchi et al., 2013), to detect bearing faults based on spectral kurtosis algorithm using simulated vibration signals. In (Zhang, Tan, & Lin 2016), gearbox body crack fault detection was studied using vibration signals collected in different train speeds. A frequency features were extracted from vibration signals using low-pass filtering technique to detect faults. Zhao and Kinnaert (2009) studied fault detection using well-known CUSUM (Taylor 2006) statistical change-point detection tool in fault detection scheme characterization. The main objective was to detect abrupt faults for DC motors using simulated time series and to present validated analytical results on fault detection scheme improvement. Bin Shams, Budman, and Duever (2011) proposed fault diagnostics methodology for chemical plants based on CUSUM algorithm combined with principal component analysis (PCA) tool using simulated data. The proposed methodology was successfully validated in fault detection, isolation, and diagnostics of chemical plants. D'Angelo et al. (2011) proposed a methodology for incipient fault detection problem based on fuzzy clustering and Bayesian change detection in induction machine stator-winding and was successfully validated on the simulated time series for fault detection.

This paper presents a generic methodology that can detect abrupt and incipient faults including a feature fusion for asset monitoring, which was not applied in the literature. The term *generic* refers to the applicability aspect of the proposed approach for both abrupt and incipient fault types. In the first step, different statistical features are extracted using descriptive statistics tools. Secondly, based on linearly-weighted data fusion algorithm, extracted features are combined to get the unique and representative feature, with an intention of enhancing information content about the system degradation. Finally, using combined feature, segmentation based subsequence time series analysis is performed to detect and extract health state transitions indicating anomalies. The fused feature is divided into different time windows using sliding-window time series segmentation tool (Keogh et al. 2003) and characteristics of each segment is analyzed separately by means of inferential statistics based on coefficient of variations (CV) (Bąkowski, Radziszewski, & Žmindak 2017) to detect faults. The results show that proposed methodology can be effectively used to detect faults from degradation signal after feature fusion for the purpose of asset diagnostics. The methodology is implemented on point machines to detect abrupt faults and on Li-ion batteries to detect incipient faults using extracted features.

The paper is organized as follows: In Section 2, the proposed methodology steps are explained in detail. Section 3 presents data collection procedure and experimental rig setup for two case studies. The results of proposed methodology are presented in Section 4. Section 5 concludes the paper.

2. METHODOLOGY

In this section, feature extraction and normalization, fusion and fault detection by segmentation will be explained in detail.

2.1. Feature extraction and normalization

Feature extraction is known as extracting useful and important information from raw data that indicates health state transitions in system degradation. In this paper time-domain based features such as, *root-mean-square (rms)*, *kurtosis*, *skewness* and *crest factor (crfactor)* are extracted and used to analyze point machine and battery degradations for fault detection. Interested readers can find detailed information about data processing and feature extraction techniques in this (Jardine, Lin, & Banjevic 2006) review paper.

Furthermore, since there are different statistical features with different degradation behavior (e.g. increasing or decreasing) in different scales, they should be properly normalized before fusion. It's important to note that, all extracted features have a valuable information about the physical health state of the component under consideration. Figure 6 and Figure 7, show extracted features from point machine and Li-ion battery degradation. An example for the features with different scaling and degradation behavior can be shown as *kurtosis* and *skewness* features for the both case studies. Therefore, before data fusion, features are put into standard scale and form by using the equations given below. Two different functions are used to normalize the features, equation (1) for the features with decreasing degradation and equation (2) for the features with increasing degradation.

$$Nf_{i,t} = \frac{f_{i,t}}{\max(f_{i,t})}; \tag{1}$$

$Nf_{i,t}$ is normalized i^{th} feature data point at time index t ($t = 1 \dots T,\ T\ is\ the\ feature\ length$).

$$Nf_{i,t} = \frac{\min(f_{i,t})}{f_{i,t}}; \tag{2}$$

After normalization process, all features have the same standard degradation behavior.

2.2. Feature fusion

Feature fusion is the process of feature combination to construct generic feature to enhance information content about the system degradation. It is very difficult to say that a single feature can perfectly represent the system degradation. Thus, it is important to combine different features to construct generic feature that preserves useful information from all features for better system diagnostics purposes. Linearly weighted average (Williard et al. 2013) which is most widely used data fusion approach in literature, is used in this study. The linearly weighted feature fusion is given in equation (3).

$$F_{t+1} = \frac{\sum_{i=1}^{N} w_{i,t} f_{i,t+1}}{\sum_{i=1}^{N} w_{i,t+1}};\ F_1 = \frac{f_{i,1}}{N} \tag{3}$$

F_t is the fused feature at time instant t ($t = 1 \dots T$), T is the length of feature f_i, where $\forall i = 1 \dots N$. N represents the total number of features in each group. In the beginning, all features are initialized with the same weight value as shown in equation (4).

$$w_{i,1} = \frac{1}{N}, \forall i = 1, \dots N \tag{4}$$

Where $w_{i,1}$ is the weight value for $\forall f$ at time $t = 1$. The weight values are updated in each iteration as shown in equation (5). As seen from the equation (5), the updating procedure is based on the estimation error $(1 - |F_t - f_{i,t}|)$. Doing so, features' divergence is minimized into its minimum level in fusion process.

$$w_{i,t+1} = (w_{i,t} + (1 - |F_t - f_{i,t}|)) \tag{5}$$

After the data fusion step, combined generic feature is segmented to detect a fault(s).

2.3. Fault detection

Time series segmentation has been applied in many research fields maturely, such as in earth science (Verbesselt et al. 2010), security (Albertetti et al. 2016) and machine fault detection (Liu et al. 2014) as well. The segmentation process is defined as decomposition of time series into homogeneous subsequences or groups based with similar characteristics. In this paper, sliding window time series segmentation technique is used due to its implementation simplicity and good performance dealing with noisy data. The sliding window (SW) technique analyzes the data points within the window by fitting a linear or polynomial model to group the subsequences. A model estimation error is compared with a predefined threshold to split the series. If the error value is smaller than the threshold, then the new data points are added to the current window for analysis. If estimation error is bigger than the threshold, then the current segmentation is stopped and the same process starts from the next data point searching for a new segment. A pseudocode for the sliding window algorithm is given in Table 1.

Since time series segmentation decomposes the series into homogenous subsequences, the segments can be used to detect health state transitions indicating anomalies in asset monitoring. The SW segmentation can produce multiple or even single segment depending on the threshold (error) value. A coefficient of variation (CV) (Bąkowski, Radziszewski, & Žmindak 2017), which is inferential statistics tool, is used in this paper for segment evaluation to detect a fault(s). One of the advantages of CV is, it has no dimension and can be used to compare data sets with different measures and different means. The CV is used to infer statistical information by measuring the dispersion of data points within a segment around the mean and can be used to compare the level of variation between two segments, even if the mean values are different. The CV is the ratio of the standard deviation, (equation (6)) to the mean (equation (7)), as given in equation (8).

$$\sigma = \sqrt{\frac{1}{M-1}\sum_{j=1}^{M}\left|S_{k,j}-\mu\right|}\ ;\forall j = 1 \ldots M \tag{6}$$

where M is the number of data points in segment S_k ($k = 1 \ldots K$). K is the total number of segments after SW algorithm.

$$\mu = \frac{1}{M}\sum_{j=1}^{M} S_{k,j}, \forall k = 1 \ldots K \tag{7}$$

$$CV = \left(\sigma/_{\mu}\right) \times 100 \tag{8}$$

By extracting the CV of decomposed features, one can determine an optimum number of segments by analyzing the CV results. If CV value for two adjacent segments is closer, then these segments can be mentioned as one segment having a similar degree of variation and different otherwise. The fault(s) or health state change(s), is then detected by extracting segment boundaries (data points) as a final step after segment evaluation. Flowchart for proposed methodology is given in Figure 1.

Table 1. Sliding Window time series segmentation.

```
segmentation (data, max_error):
anchor=1;
while not segmented data
% w: window size
w=2;
% err: estimated model error
 if err (data(anchor:anchor+w))<max_error
   w=w+1;
 else
%convert into segment
   data_segments <- data (anchor:
anchor+(w-1));
%update anchor with new data point
   anchor= anchor+w;
 end
end
```

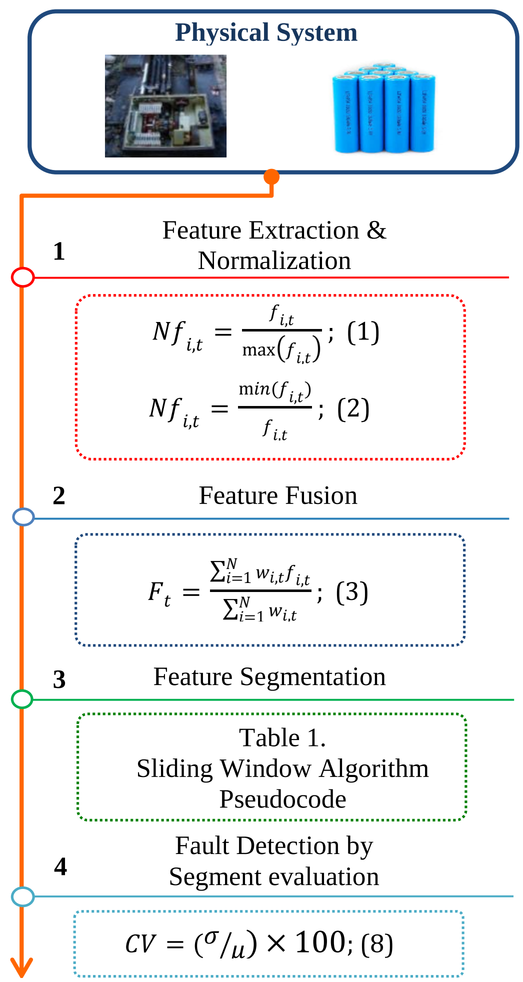

Figure 1. Fault detection methodology flowchart.

3. ILLUSTRATIVE CASE STUDIES

This section explains experimental rig setup and data collection procedures for point machine and Li-ion battery condition monitoring.

3.1. Point machine monitoring

Point machines are used to manage railway turnouts by changing train tracks at a distance. An electro-mechanical point machine which is investigated in this current work for abrupt fault detection is shown in Figure 2.

The point machine diagnostics is a very challenging task due to its complex structure, working conditions and inaccessible failure modes that occur in a long period of time (Gebraeel, Elwany, & Pan 2009). Thus, sliding-chair failure, which is the most frequently seen failure mode, is artificially generated and collected from the real point machine system (see Figure 2). The sliding-chairs are the metal plates installed on the turnout system, that support to drive the rail blades from one side to another. Initially, there are totally 12 sliding-chair plates in a healthy state (lubricated) on the turnout system. The farthest 10th, 11th and 12th plates from the point machine was contaminated manually to simulate the first faulty state. Contaminating the 9th farthest plate in the second step generates the second faulty state. Contamination process continued by following the same procedure until all plates were fully contaminated to generate the sliding-chair failure. Finally, we obtained 10 different health states (10 data samples in each state) of sliding-chair degradation. DC motor current time series, which is depicted in Figure 3, were used in this paper due to its good failure representation property (Ardakani et al. 2012; Camci et al. 2016). In Figure 3, *'health state-1'* indicates the healthy state before contamination process and the rest of them indicate faulty states for sliding-chair degradation. The current curves are further used to extract statistical features to detect the abrupt fault(s) where the machine stepped into the faulty state.

Figure 2. Electro-mechanical point machine.

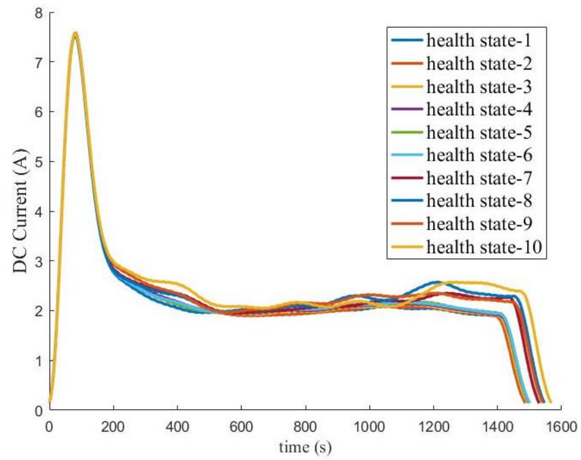

Figure 3. Sliding-chair degradation.

3.2. Li-ion battery health monitoring

Li-ion batteries have been used to store the energy in different applications today, being as one of the most critical components of the complex systems. Battery state-of-health (SoH) estimation (Camci et al. 2015), feature evaluation/selection (Atamuradov and Camci 2016; Williard et al. 2013) and prognostics (Wang, Miao, & Pecht 2013) have been widely studied in the literature for battery health management. The LiFePO4 type battery with the capacity 0.6Ah and nominal voltage of 3.2V is used in this study. The battery was aged using the accelerated aging procedure in the climatic chamber under constant 45 *°C* in the laboratory. The accelerated aging procedure was stopped when the battery reached to SoH value of 80%. This value is accepted as the complete failure threshold for the Li-ion batteries (Wang, Miao, & Pecht 2013). In each 10 cycles, the battery SoH was checked to see if the battery reached its threshold value. One (1) cycle includes completely charging and discharging steps. Experimental rig for battery health monitoring is shown in Figure 4. The battery testing system logged different measurements during the aging process. Raw discharge voltage curves were further processed in feature extraction step to analyze and detect an incipient fault(s). As Li-ion battery ages, it causes the discharging process to accelerate.

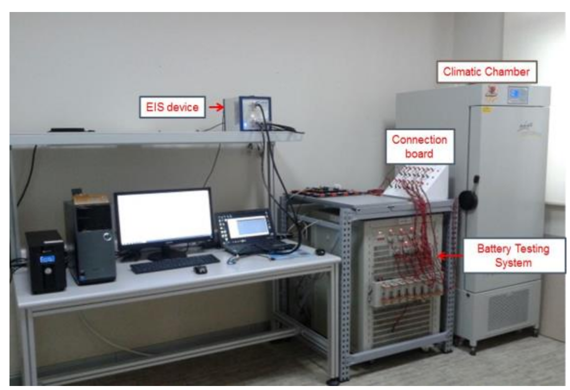

Figure 4. Battery aging experimental rig.

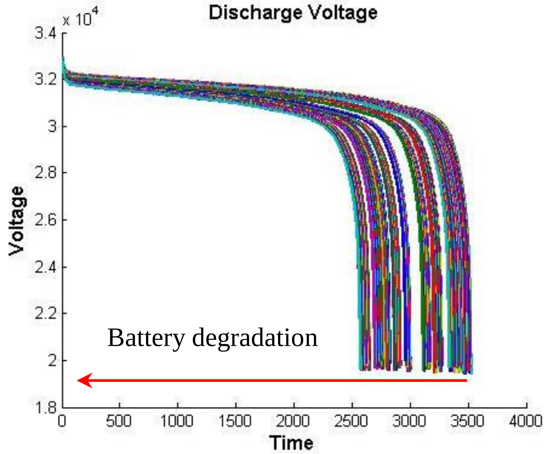

Figure 5. Li-ion discharge voltage curves indicating battery aging.

The discharge acceleration process can be seen from the discharge voltage curve degradations (from right to left) which are shown in Figure 5 indicating the battery aging. As the battery degrades, discharge voltage curve length decreases by time.

4. RESULTS AND DISCUSSIONS

The point machine DC current curves and Li-ion discharge voltage measurements went through feature extraction step to extract the descriptive statistics as shown in Figure 6 and Figure 7. Since the *'skewness'* has negative values, it was converted into positive values by taking the absolutes before normalization step for both case studies. The features *rms*, *kurtosis*, and *skewness* were normalized using equation (1) and *crest factor* was normalized by using the equation (2). The normalized features are displayed in Figure 8. In battery health assessment, normalized feature should have the numbering scale between 1 (100% SoH) and 0.80 (80% SoH is battery failure threshold). But the features *rms* and a *crest factor* in Figure 8 (b), did not behave in this pattern with the scaling between 1 and 0.98, and these normalized features could lead to wrong SoH estimation in battery health assessment. Due to this inconsistency, *rms* and *crest factor* features were excluded from feature fusion process in incipient fault detection. Using linearly weighted feature fusion algorithm (equation (3)), point machine and Li-ion battery normalized features were combined to get a generic feature that preserves a global information about the component degradation. Smoothing was conducted to filter the noise from combined features. The feature fusion results are shown in Figure 9. Furthermore, feature segmentation was applied on smoothed fused feature, using SW segmentation technique to decompose the given feature into homogenous subsequences to extract the within health state changes. Since sliding-chair degradation was simulated in 10 different health states, the combined feature was segmented into 10 different segments by optimizing the error threshold manually. As for the case of battery degradation, it's hard to express segmentation process with any physical meaning during the accelerated aging procedure. Nevertheless, combined feature indicating battery health state was divided into 4 segments. The CV and the mean statistics were extracted for point machine and battery which is given in Figure 11 and Figure 12. The figures contain not only the CV values but the segment means to show the difference and the usefulness of dispersion statistics. As seen from the Figure 11(b), within segment mean values do not reflect any abrupt health state changes while sliding-chair degrades. Interpreting the CV values depicted in Figure 11(b), show that dispersion within the segments displays an instant change after the 3rd segment, indicating an abrupt fault in sliding-chair failure propagation. Based on this inferences,

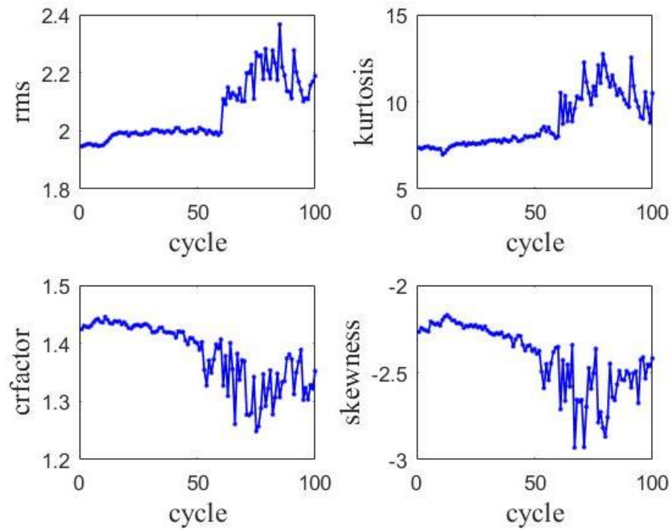

Figure 6. Extracted features from point machine DC current.

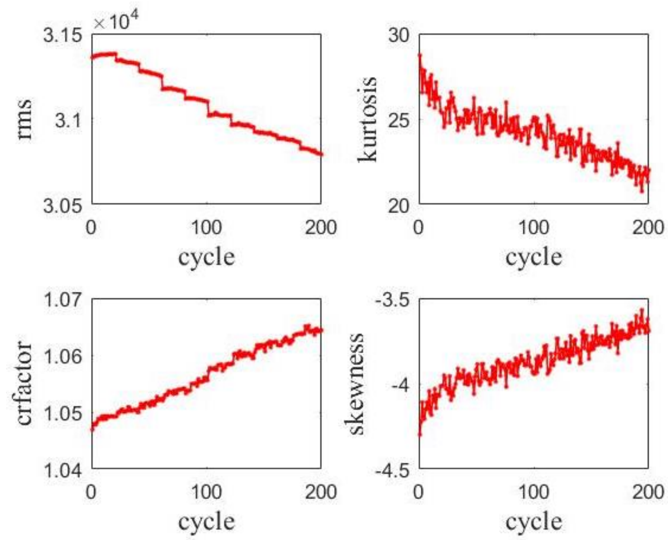

Figure 7. Extracted features from battery discharge voltage.

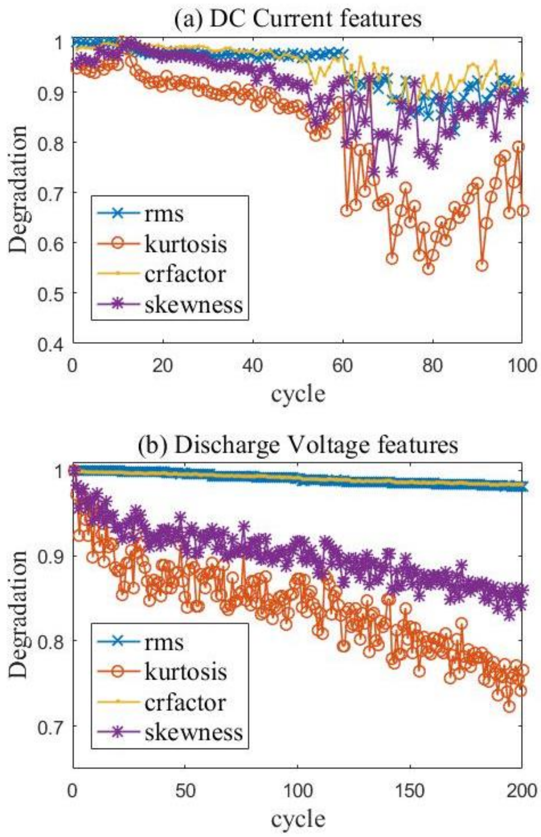

Figure 8. Normalized features.

first three segments can be assumed as healthy and rest of them as faulty segments (or as system failure) for the case of sliding-chair degradation. The instant change in battery health state is seen perfectly in CV values (Figure 12(a)) rather than the mean values. A segment where the fault develops incipiently in battery degradation can be defined as the 3rd segment (Figure 12(a)). Numerical differences between two adjacent segments and their mean value for the point machine and battery CV statistics are depicted in Figure 13. The reason for not plotting the mean differences for point machine and battery, was that they did not show any significant changes. As seen from the given figures, the health state changes can be easily detected from the CV differences. The mean values (dashed line in Figure 13) of CV differences can be also used as the threshold indicating the fault in the system. Consequently, an inferential CV statistic can thus be used for fault detection and segment evaluation for point machine and battery health state monitoring effectively.

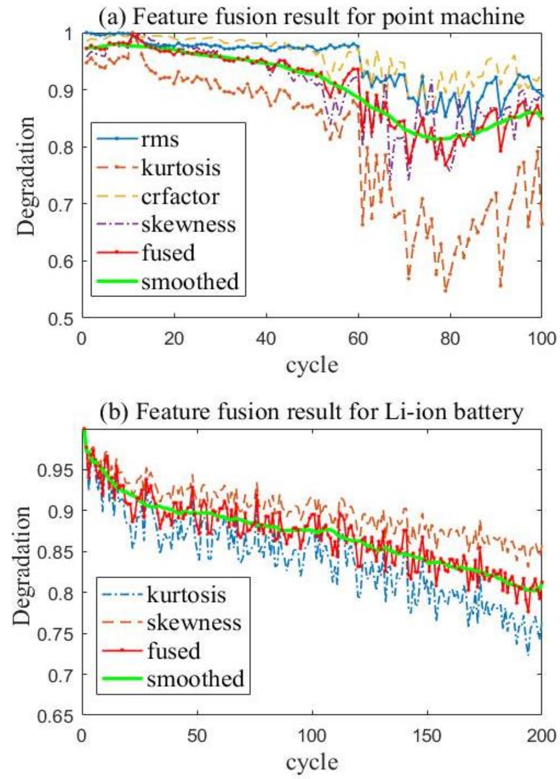

Figure 9. Fusion results for point machine and battery.

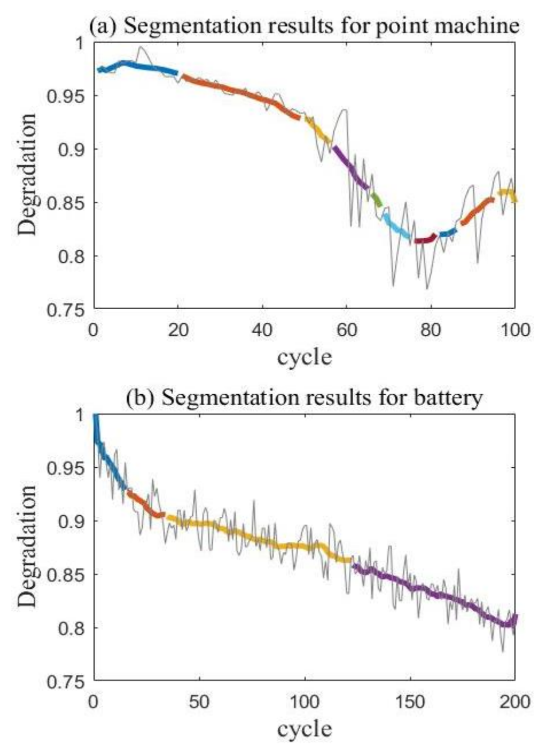

Figure 10. SW segmentation results.

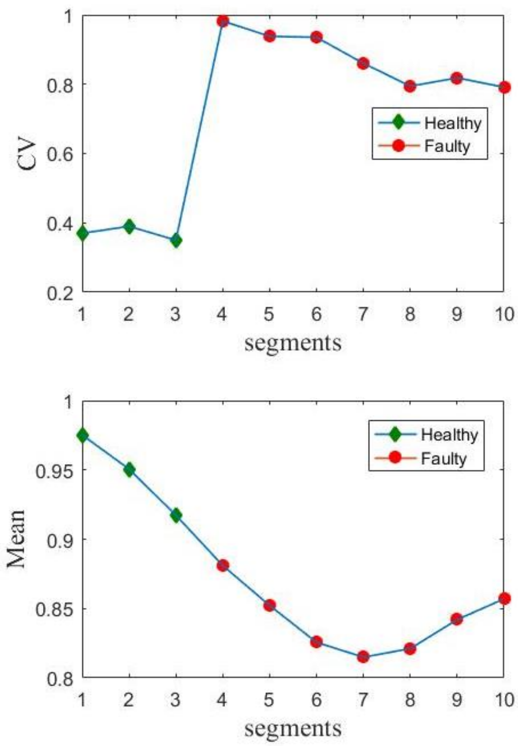

Figure 11. Within segment (a) CV and (b) mean values for point machine feature.

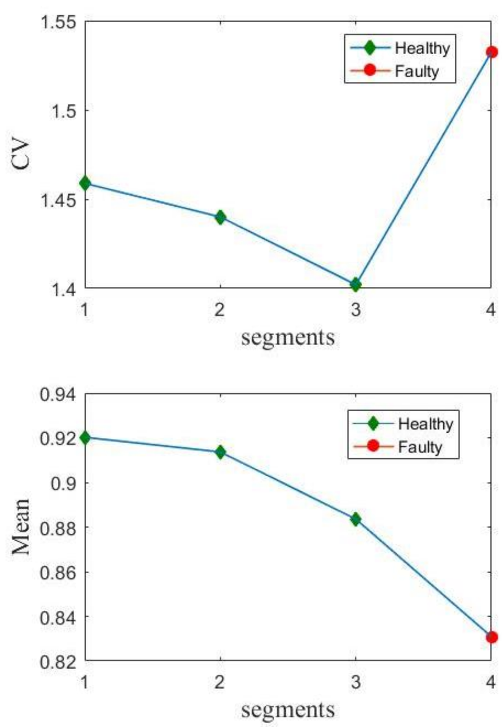

Figure 12. Within segment (a) CV and (b) mean values for battery feature.

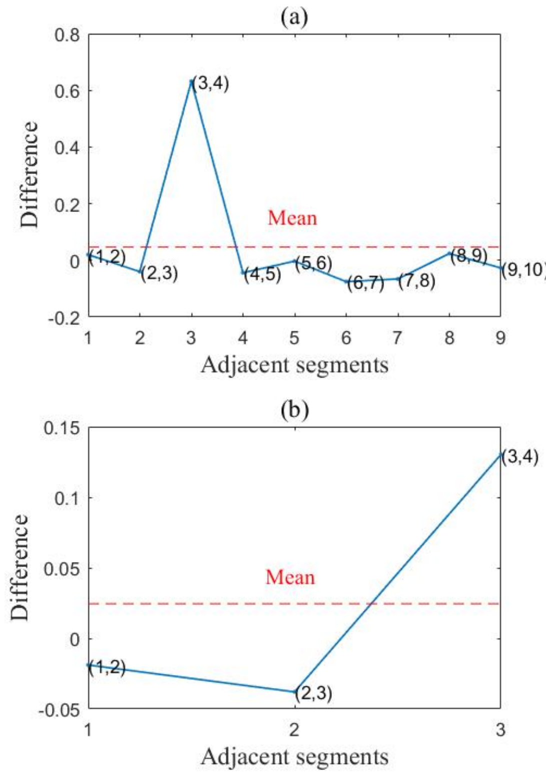

Figure 13. (a) point machine CV differences, (b) battery CV differences.

5. CONCLUSION

In this paper, a generic methodology for detecting incipient and abrupt faults was developed and its effectiveness was shown on two real case studies. The main achievements of this methodology can be concluded as follows:

- The information content of asset degradation was enhanced by means of feature fusion.
- Time series segmentation was used to decompose degradation feature into homogenous groups to be analyzed in fault detection.
- Inferential statistics, which is the coefficient of variation (CV), was used to detect faults by analyzing the degradation segments. In addition to fault detection, CV values can be also used in segment evaluation to get an optimum segment number in time series analysis.
- Proposed fault detection methodology can be used for abrupt and incipient fault types.

Calculation of CV is impossible if the mean value is zero, which is accepted as a disadvantage. The CV can give reasonable results if the all variables are positive. For the future work, this methodology will be extended by developing robust feature fusion algorithm next to employing frequency-domain, time-frequency domain feature extraction and segment evaluation techniques in fault detection for machine failure prognostics.

ACKNOWLEDGEMENT

This research was supported by a grant from ENIT, Production Engineering Laboratory (LGP), funded by ALSTOM. Point machine and Li-ion degradation datasets were taken from the projects (# 108M275 and # 113M093), which were supported by The Scientific and Technological Research Council of Turkey (TUBITAK).

REFERENCES

Albertetti, Fabrizio, Lionel Grossrieder, Olivier Ribaux, and Kilian Stoffel. 2016. "Change Points Detection in Crime-Related Time Series: An on-Line Fuzzy Approach Based on a Shape Space Representation." *Applied Soft Computing Journal* 40: 441–54. http://dx.doi.org/10.1016/j.asoc.2015.12.004.

Ardakani, Hossein Davari et al. 2012. "PHM for Railway System - A Case Study on the Health Assessment of the Point Machines." *PHM 2012 - 2012 IEEE Int. Conf.on Prognostics and Health Management: Enhancing Safety, Efficiency, Availability, and Effectiveness of Systems Through PHM Technology and Application, Conference Program*: 1–5.

Atamuradov, Vepa, and Fatih Camci. 2016. "Evaluation of Features with Changing Effectiveness for Prognostics." *Annual Conference of the Prognostics and Health Management Society 2016*.

Bąkowski, Andrzej, Leszek Radziszewski, and Milan Žmindak. 2017. "Analysis of the Coefficient of Variation for Injection Pressure in a Compression Ignition Engine." *Procedia Engineering* 177: 297–302. http://linkinghub.elsevier.com/retrieve/pii/S18777058 1730735X.

Camci, F., O. F. Eker, S. Baskan, and S. Konur. 2016. "Comparison of Sensors and Methodologies for Effective Prognostics on Railway Turnout Systems." *Proceedings of the Institution of Mechanical Engineers, Part F: Journal of Rail and Rapid Transit* 230(1): 24–42. http://pif.sagepub.com/lookup/doi/10.1177/09544097 14525145.

Camci, F, C Ozkurt, O Toker, and V Atamuradov. 2015. "Sampling Based State of Health Estimation Methodology for Li-Ion Batteries." *Journal of Power Sources* 278: 668–74.

D'Angelo, Marcos F S V et al. 2011. "Incipient Fault Detection in Induction Machine Stator-Winding Using a Fuzzy-Bayesian Change Point Detection Approach." *Applied Soft Computing Journal* 11(1): 179–92.

Gebraeel, Nagi, Alaa Elwany, and Jing Pan. 2009. "Residual Life Predictions in the Absence of Prior Degradation Knowledge." *IEEE Transactions on Reliability* 58(1): 106–17.

ISO 13372:2012. "Condition Monitoring and Diagnostics of Machines-Vocabulary." http://viewer.afnor.org/Pdf/Viewer/?token=VR4Vvnpr APA1.

Jardine, A. K S, Daming Lin, and Dragan Banjevic. 2006. "A Review on Machinery Diagnostics and Prognostics Implementing Condition-Based Maintenance." *Mechanical Systems and Signal Processing* 20(7): 1483–1510.

Keogh, E, S Chu, D Hart, and M Pazzani. 2003. "Segmenting Time Series: A Survey and Novel Approach." *Data Mining in Time Series Databases*: 1–21.

Liu, Junqiang, Malan Zhang, Hongfu Zuo, and Jiwei Xie. 2014. "Remaining Useful Life Prognostics for Aeroengine Based on Superstatistics and Information Fusion." *Chinese Journal of Aeronautics* 27(5): 1086–96. http://dx.doi.org/10.1016/j.cja.2014.08.013.

Pennacchi, Paolo et al. 2013. "Experimental Evidences in Bearing Diagnostics for Traction System of High Speed Trains." *Chemical Engineering Transactions* 33: 739–44.

Bin Shams, M. A., H. M. Budman, and T. A. Duever. 2011. "Fault Detection, Identification and Diagnosis Using CUSUM Based PCA." *Chemical Engineering Science* 66(20): 4488–98. http://dx.doi.org/10.1016/j.ces.2011.05.028.

Taylor, Wayne A. 2006. "Change-Point Analysis: A Powerful New Tool For Detecting Changes." *Analysis*: 1–19.

Verbesselt, Jan, Rob Hyndman, Glenn Newnham, and Darius Culvenor. 2010. "Detecting Trend and Seasonal Changes in Satellite Image Time Series." *Remote Sensing of Environment* 114(1): 106–15. http://dx.doi.org/10.1016/j.rse.2009.08.014.

Wang, Dong, Qiang Miao, and Michael Pecht. 2013. "Prognostics of Lithium-Ion Batteries Based on Relevance Vectors and a Conditional Three-Parameter Capacity Degradation Model." *Journal of Power Sources* 239: 253–64. http://linkinghub.elsevier.com/retrieve/pii/S03787753 13005235.

Williard, N;, W; He, M; Osterman, and M Pecht. 2013. "Comparative Analysis of Features for Determining State of Health in Lithium-Ion Batteries." *Int. J. Progn. Health Manag* 2013(4): 1–7.

Wu, Yunkai, Bin Jiang, Ningyun Lu, and Donghua Zhou. 2015. "ToMFIR-Based Incipient Fault Detection and Estimation for High-Speed Rail Vehicle Suspension System." *Journal of the Franklin Institute* 352(4):

1672–92. http://www.sciencedirect.com/science/article/pii/S0016003215000599.

Zhang, Bing, Andy C C Tan, and Jian hui Lin. 2016. "Gearbox Fault Diagnosis of High-Speed Railway Train." *Engineering Failure Analysis* 66: 407–20. http://dx.doi.org/10.1016/j.engfailanal.2016.04.020.

Zhao, Qing, and Michel Kinnaert. 2009. "Statistical Properties of CUSUM Based Fault Detection Schemes for Fault Tolerant Control." *Proceedings of the 48h IEEE Conference on Decision and Control (CDC) held jointly with 2009 28th Chinese Control Conference*: 7831–36. http://ieeexplore.ieee.org/lpdocs/epic03/wrapper.htm?arnumber=5400825.

BIOGRAPHIES

Vepa Atamuradov was born in Turkmenistan in 1986. He received his Ph.D. in Electrical-Computer Engineering from Selçuk University (2016), MS in Computer Engineering from Fatih University (2009) in Turkey. He actively worked as an RA in both "Development of Failure Prognostics and Maintenance Planning System for Point Mechanisms in Railway (2008-2009)" and "Development of Design based State-of-Health and Remaining Useful Life Estimation Techniques for Battery Management Systems and Its Application to Rechargeable Batteries (2014-2016)" projects, granted by The Scientific and Technological Research Council (TUBITAK) of Turkey. Currently, he is working as a Postdoc research fellow on PHM of high-speed train bogies at Tarbes National School of Engineering (ENIT), France, since July 2016. His research interests include failure diagnostics and prognostics of Industrial systems using Machine Learning and Statistical Methods.

Kamal Medjaher is Professor at Tarbes National School of Engineering (ENIT), France, since February 2016. He conducts his research activities within the Production Engineering Laboratory (LGP). Before this position, he was Associate Professor at the National Institute of Mechanics and Microtechnologies in Besançon, France, from September 2006 to January 2016. After receiving an engineering degree in electronics, he received his MS in control and industrial computing in 2002 at "Ecole Centrale de Lille" and his Ph.D. in 2005 in the same field from University of Lille 1. Since September 2006, Kamal Medjaher leads research works in the field of Prognostics and Health Management of industrial systems.

Benjamin Lamoureux was born in France in 1986. He received both a Master's Degree in Mechatronics from the University Pierre & Marie Curie and a Master's Degree in Engineering from Arts & Métiers ParisTech in Paris in 2010. From 2011 to 2014, he performed an industrial Ph.D. work in collaboration between Arts & Métiers ParisTech and SAFRAN Aircraft Engines Villaroche (formerly SAFRAN Snecma). He received his Ph.D. in June 2014. In October 2014, he joined the PHM department of Alstom Saint-Ouen to extend his Ph.D. research in the railway domain, and he still occupies the same position today. His current research interests are machine learning, statistics, data science and computer science applied to PHM.

Pierre Dersin received his Ph.D. in Electrical Engineering from MIT (1980), MS in O.R. also from MIT. Engineer and Math BS from Brussels University, Belgium. Since 1990 with ALSTOM Transport, he has occupied several positions in RAMS, Maintenance and R&D. Currently RAM (Reliability-Availability-Maintainability) Director and PHM (Prognostics & Health Management) Director of ALSTOM Digital Mobility (the part of ALSTOM which acts as a catalyst for the 'digital revolution'). Also, Leader of ALSTOM 's Reliability & Availability Core Competence Network. Since April 2014, co-Director of the joint ALSTOM-INRIA Research Laboratory for digital technologies applied to mobility and energy. Prior to joining ALSTOM, he had worked on fault diagnostic systems for factory automation (with Engineering firm Fabricom), and earlier, at MIT LIDS, studied the reliability of electric power grids, as part of the Large Scale System Effectiveness Analysis Program funded by the US Department of Energy. His current research interests include the links between reliability engineering and PHM and the application of data science, machine learning and statistics to both fields, as well as systems optimization and simulation, including systems of systems. He is a member of the IEEE Reliability Society's Administrative Committee and IEEE Future Directions Committee and, as of January 2017, will be the IEEE Reliability Society Vice-President for Technical Activities. He was a Keynote speaker at the 2nd European PHM Conference, Nantes, July 2014.

Noureddine Zerhouni received the Engineering degree from the National Engineers and Technicians Institute of Algiers, Algiers, Algeria, in 1985, and the Ph.D. degree in automatic control from the Grenoble National Polytechnic Institute, Grenoble, France, in 1991. He joined the National Engineering Institute of Belfort, Belfort, France, as an Associate Professor in 1991. Since 1999, he has been a Full Professor with the National Institute in Mechanics and Microtechnologies, Besançon, France. He is a member of the Department of Automatic Control and Micro-Mechatronic Systems at the FEMTO-ST Institute, Besançon. He has been involved in various European and national projects on intelligent maintenance systems. His current research interests include intelligent maintenance, and prognostics and health management.