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Quantitative Evaluation of Electric Features for Health Monitoring and Assessment of AC-Powered Solenoid Operated Valves ⋆

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Abstract: Quantitative assessment of feature performance for health monitoring is key to feature selection. This paper illustrates the application of well-established metrics in the research community - namely, monotonicity, robustness and prognosability - to the quantitative performance assessment of features for health monitoring of alternating-current (AC) powered solenoid operated valves (SOVs). These features are extracted from voltage and current signals measured on the valves and builds on previous work of the authors. Based on these metrics, the appropriate features are selected to be used as condition indicators. The selected features are inputs to a logistic regression model to predict a health index ranging from 0 to 1, which can be easily monitored and assessed by non-experts. We demonstrated the developed methodology on the experimental data acquired from accelerated life tests on 48 identical AC-powered SOVs.

Keywords: Solenoid Valves, Logistic Regression, Condition Monitoring, Prognostics and Health Management.

1. INTRODUCTION

Since solenoid operated valves (SOVs) are critical components in many industrial applications, there has been a growing interest in developing technologies to support the implementation of the Condition Based Maintenance (CBM) or Predictive Maintenance (PdM) strategies for SOVs, see Jameson et al. (2014). These required technologies comprise sensing, data acquisition, condition indicator (CI) construction, health assessment, and remaining useful life (RUL) prediction. Some technologies based on various non-invasive sensing techniques, such as current and voltage sensors, vibration sensors, 77GHz frequency modulated continuous wave (FMCW) millimeter-wave radar, have been proposed in the literature, for examples see Kryter (1992); Guo et al. (2016); Li et al. (2021); Tod et al. (2023). The technologies based on current and voltage signals are preferred in the industry because the sensors installation is relatively easy.

There is extensive literature on electrical signal based condition monitoring (CM) and prognosis and health management (PHM) technologies for direct current (DC) powered SOVs, see Perotti (2010); Daigle and Goebel (2011); Filho and Negri (2013); Jo et al. (2020); Tang et al. (2019). However, the development of electrical signal based CM and PHM technologies for AC-powered SOVs is still very limited and has gained some interest since the last decade, see Mazaev et al. (2020); Utah and Jung (2020); Ompusunggu and Hostens (2021); Tod et al. (2023).

An important step in the development of CM and PHM technology lies in determining features or condition indicators (CIs) extracted from the sensor signals. These features are useful for diagnostics or tracking the degradation progress of critical assets/ components under investigation. Prospective features for critical components, like rolling element bearings, have been quantitatively evaluated and reported by various researchers in the literature, for example, see Kumar et al. (2021); Oh et al. (2022). However, according to the authors' knowledge, there is not yet a published work discussing the quantitative evaluation of prospective features for AC-powered SOVs.

In our previous works, three different methods to extract a number of prospective features from the electrical signals measured on AC-powered SOVs, namely (i) the first-principle model based method Tod et al. (2023), (ii) the statistics-based method Mazaev et al. (2020), and (iii) the physics-inspired feature engineering based method Ompusunggu and Hostens (2021), have been proposed and demonstrated on the datasets obtained from accelerated life test (ALT) campaigns on 48 identical AC-powered SOVs. The experimental results showed that some features are good for diagnostic purposes, namely to identify the type of failure modes occurring in the valves, while others display systematic changes during the AC-powered SOV's

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lifetime, which is good for health assessment and prognosis.

1.1 Aim and Scope

The aim of this paper is to quantitatively assess the performance of all the prospective features extracted with the three aforementioned methods. By doing so, the most relevant features can be selected in an objective manner. The selected features are then fused into a health index (HI) that represents the overall health status of the valves. Notably, the selected CIs can also be used for prognosis, but it is out of the scope of this paper.

1.2 Paper Organisation

The remainder of this paper is structured as follows. In Section 2, we propose the methodology to quantitatively assess the performance of the prospective features extracted using three different approaches. In Section 3, we briefly introduce the test setup and the accelerated life test campaign of 48 identical AC-powered SOVs. Section 4 is a discussion on the quantitative performance of all the prospective features obtained after applying the proposed methodology, based on which we select the most relevant features for the health assessment of AC-powered SOVs. In Section 5, we discuss some conclusions drawn from this work and propose future work.

2. METHODOLOGY

The overall methodology proposed in this paper is illustrated in the flowchart in Figure 1. It consists of three main steps comprising (i) Prospective features extraction from raw electrical signals, (ii) Relevant feature selection and (iii) Feature fusion for health assessment. *In the first step*, three set of prospective features are computed from the measured current signal $i(t)$ and voltage signal $u(t)$ based on three aforementioned methods, which are briefly discussed in the following sub-section. *In the second step*, the computed features are quantitatively assessed using three established metrics for prognostic features selection, namely (i) **Monotonicity**, (ii) **Robustness** and (iii) **Prognosability**. The arithmetic average of the three metrics is computed, yielding an overall score which is used for the feature selection. *In the third step*, the selected features are fused into a single value, namely a health index (HI), using a **logistic regression** (LR) technique. Notably, the output of the LR model, i.e. the HI, ranges between 0 and 1, thus allowing an easy and intuitive assessment of the health status of AC-powered SOVs.

2.1 Feature Extraction

Three different methods for feature extraction from the AC-powered SOV's electrical signals have been applied in previous work, namely based on (i) a first-principle model, (ii) physics-inspired signal processing and (iii) a statistical technique. We briefly recapitulate them in the next paragraphs.

Let $i(t)$ and $u(t)$ be the analog current and voltage signals, respectively, measured on an AC-powered SOV. Both signals were acquired through digital data acquisition, so

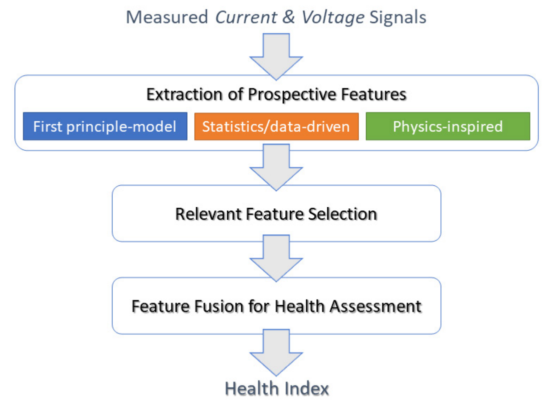


Fig. 1. The overall methodology.

we denote the digitized current and voltage with i_k and u_k, respectively, with $k = 1, 2, ..., n$ the sampling indices.

First-principle model-based features In our previous work Tod et al. (2023), we built a first-principle model of AC-powered SOVs by coupling the electromagnetic and mechanic behaviour and we improved this model by taking into account shading ring fracture and wear of the plunger, two common reasons for degradation of AC-powered SOVs. The improved model is schematically shown in Figure 2. Readers interested in the details of this model are referred to the previous publication Tod et al. (2023).

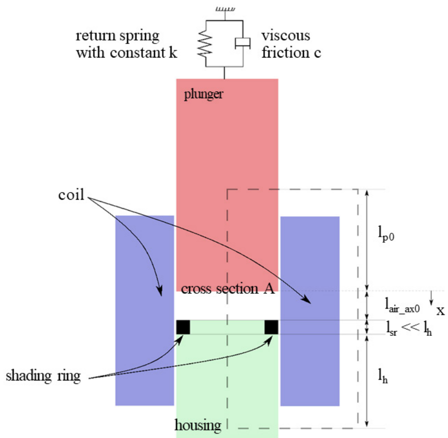
We identified shading ring force and Coulomb friction force as indicators for degradation of shading ring or plunger, respectively. Through estimation of the shading ring force and Coulomb friction force from the measured current signal i_k and voltage signal u_k, we established physical features or CIs.

Note that the improved first-principle model combined with measured current and voltage also allows us to estimate the displacement of the plunger, which represents the AC-powered SOVs' health status. Therefore, next to the shading ring and kinetic Coulomb friction forces, we also considered two other features as CIs: the area under the plunger movement curve and the average of the plunger travel end. In summary, we established four physical features or CIs extracted from the electric signals and the first-principle model, which are summarized in Table 1.

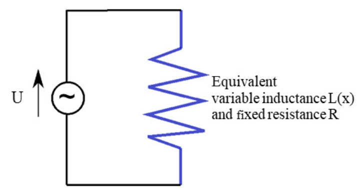
Table 1. Physical features.

Feature	Description
$F_{Coulomb}$	Kinetic Coulomb friction force
$F_{Shading}$	Shading ring force
$AUDispC$	Area under the curve of the plunger movement
$DispAve$	Average of the plunger travel end

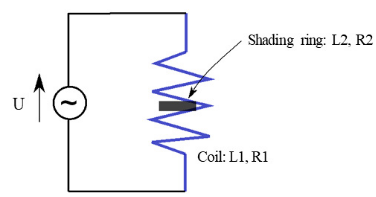
Statistics-based features As the input voltage signal u_k applied to the SOVs is always the same, it is only the current signal i_k that changes as the degradation progresses. A deviation of the current signal at a given condition i_k from its reference current signal at a healthy condition i_k^h could also be an indicator of degradation in SOVs. To quantify this deviation, let $\epsilon_k = i_k - i_k^h$ be defined as the current signal deviation.



(a) Main components comprising the main coil, the housing, the return spring and the shading ring.



(b) An equivalent circuit without considering the shading ring.



(c) An equivalent circuit by isolating the coil and the shading ring.

Fig. 2. Graphical representation of an AC-powered SOV, reproduced from Tod et al. (2023).

In this paper, some statistical features are computed from the measured current signal i_k and the current signal deviation ϵ_k, as summarised in Table 2.

Table 2. Statistical features.

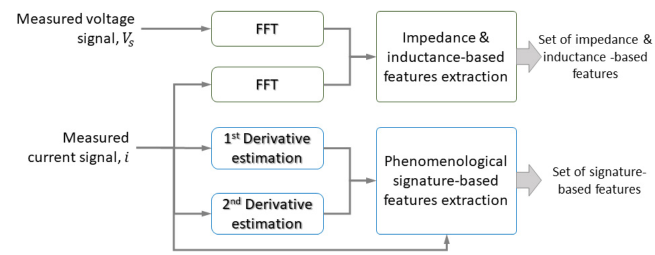
Feature	Description
$curr\_rms$	Root mean square (rms) of the *raw* current signal i_k
$curr\_kurt$	Kurtosis of the *raw* current signal i_k
$curr\_cf$	Crest factor of the *raw* current signal i_k
Res_curr_rms	Root mean square (rms) of the current signal deviation ϵ_k
Res_curr_kurt	Kurtosis of the current signal deviation ϵ_k
Res_curr_cf	Crest factor of the current signal deviation ϵ_k

Physics-inspired features Inspired by the profound understanding of the effects of the degradation on the electromechanical behavior of AC-powered SOVs through the improved first-principle model and the underlying phenomena, some features were defined and a methodology to extract those features from the measured current and voltage signals was proposed in our previous work Ompusunggu and Hostens (2021). Figure 3 graphically illustrates the features extraction methodology.

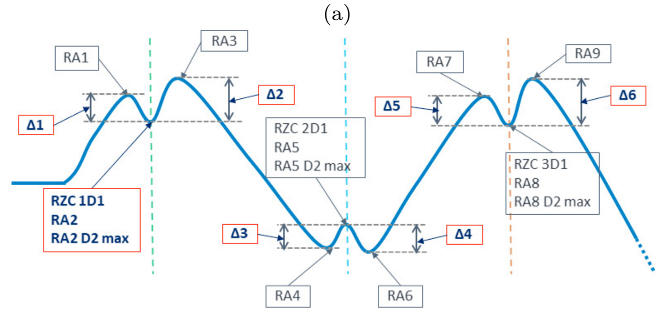
The impedance spectrum $Z(\omega)$ is defined as the ratio between the voltage spectrum $V(\omega)$ and the current spectrum $I(\omega)$:

$$Z(\omega) = \frac{V(\omega)}{I(\omega)} = \frac{FFT\,[u(t)]}{FFT\,[i(t)]}, \tag{1}$$

where FFT denotes the fast Fourier transformation. The inductance spectrum $L(\omega)$ is obtained by taking the imaginary part of the impedance spectrum, i.e. $L(\omega) = \mathrm{Im}\,([Z(\omega)])$. Some potential features for condition monitoring purposes can be extracted based on the magnitudes of the impedance and inductance spectra at the AC-source frequency ω_s and its higher harmonics. The summary of the physics-inspired features is listed in Table 3.



(a)



(b)

Fig. 3. Calculation of physics-inspired features.

Table 3. Physics-inspired features.

Feature	Description
$ImFund$	The impedance spectrum magnitude at the fundamental AC-source frequency, $\lvert Z(\omega_s)\rvert$
$IdFund$	The inductance spectrum magnitude at the fundamental AC-source frequency, $\lvert L(\omega_s)\rvert$
$ImOdHarm$	Averaged impedance spectrum magnitudes at odd harmonics of the AC-source frequency, $\sum_{k=1}^{3}\lvert Z((2k+1)\times\omega_s)\rvert$
$ImEvHarm$	Averaged impedance spectrum magnitudes at odd harmonics of the AC-source frequency, $\sum_{k=1}^{3}\lvert Z(2k\times\omega_s)\rvert$
$IdOdHarm$	Averaged impedance spectrum magnitudes at odd harmonics of the AC-source frequency, $\sum_{k=1}^{3}\lvert L((2k+1)\times\omega_s)\rvert$
$IdEvHarm$	Averaged impedance spectrum magnitudes at odd harmonics of the AC-source frequency, $\sum_{k=1}^{3}\lvert L(2k\times\omega_s)\rvert$
$RZC1D1$	The first valley position, see Fig. 3
$RA2D2max$	The maximum amplitude of the 2^{nd} derivative of the current signal, $d^2i(t)/dt^2$, around the first valley, see Fig. 3
$Delta12$	$\Delta1 + \Delta2$, see Fig. 3
$Delta34$	$\Delta3 + \Delta4$, see Fig. 3
$Delta56$	$\Delta5 + \Delta6$, see Fig. 3
$CurrHiSpectHarm$	The sum of the higher harmonics of the normalised current spectrum $\mathbf{SHHCS} = \sum_{k=2}^{6}\lvert\hat{H}_I\,(k\omega_s)\rvert$

2.2 Feature Selection Methodology

Since in general the value of each relevant feature is calculated from measurement data that is periodically acquired at a predefined time interval Δt, it is therefore convenient to treat the feature values as a discrete-time series quantity. Let $\boldsymbol{X} = [x_1, ..., x_i, ..., x_N]$ be the vector representing the discrete-time series feature and $\boldsymbol{T} = [t_1, ..., t_i, ..., t_N]$ be the time vector corresponding to the feature vector, where $t_i = i\Delta t$.

Monotonicity As degradation is typically an irreversible process (no self-healing), a relevant feature is the one that has a strong correlation with time. The Monotonicity metric evaluates this trend information and shows which feature has degradation information of the asset, see Coble (2010). Since degradation of machinery evolves typically very non-linear with time, Spearman's correlation is chosen because it is robust to such non-linearity. Hence, the Monotonicity metric is defined as the absolute value of Spearman's correlation between feature and time, mathematically expressed as, see Carino et al. (2015):

$$\mathrm{Mon}(X) = \left|1 - \frac{6\sum_{n=1}^{N}(\tilde{X_n} - \tilde{T_n})}{N(N^2-1)}\right| \tag{2}$$

where $\tilde{X_n}$ and $\tilde{T_n}$ are the rank sequences of X and T.

Robustness When an engineering asset exhibits a stochastic process, a good feature should be robust to outliers and noise. The robustness of a feature X is defined as, for example see Kumar et al. (2021):

$$\mathrm{Rob}(X) = \frac{1}{N}\sum_{n=1}^{N}\exp\left(-\left|\frac{x_n - \bar{x_n}}{x_n}\right|\right) \tag{3}$$

where x_n is the feature value at the time index t_n and $\bar{x_n}$ is the mean trend value of the feature which is acquired through the smoothing process.

Prognosability Prognosability is a metric related to the consistency of the different end-of-life (EoL) feature values across the fleet. It is defined as the variability of the EoL feature values relative to the range between initial and final feature values, see Coble (2010). In the formula, this reads:

$$\mathrm{Prog}(X) = \exp\left(-\frac{\mathrm{std}\left(X_j\left(N_j\right)\right)}{\mathrm{mean}\left|X_j\left(1\right) - X_j\left(N_j\right)\right|}\right), j = 1\ldots M \tag{4}$$

where the index j is the asset number, X_j represents the vector of measurements of a feature on the j^{th} asset, N_j is the number of measured values of the feature on the j^{th} asset and M is the number of monitored assets.

Overall performance The overall performance of each feature $P_{Overall}(X)$ is assessed by taking the arithmetic mean of those metrics being defined as follows:

$$P_{Overall}(X) = \frac{\overline{\mathrm{Mon}(X)} + \overline{\mathrm{Rob}(X)} + \mathrm{Prog}(X)}{3}, \tag{5}$$

where $\overline{\mathrm{Mon}(X)}$ and $\overline{\mathrm{Rob}(X)}$ represent the mean monotonicity and robustness metric, respectively.

2.3 Logistic-Regression (LR) Based Health Assessment

In the maintenance engineering context, a health assessment is the determination of the health status of critical assets/components. It is custom to quantify the health status with a binary value, *e.g.* **0** or **1**, where this categorical value may be seen as a health index (HI). For AC-powered SOVs health assessment purposes, one could consider that the HI of (close to) 1 represents a healthy state, on the contrary, the HI of (close to) 0 represents a failure state. This justifies that the HI progressively changes from 1 to 0 as the valves degrade.

The feature values are not necessarily restricted between 0 and 1, which cannot allow a direct justification and easy interpretation of the health status of the SOVs by non-experts (i.e. operators). To this end, the feature values evolving from a healthy to a failure state need to be transformed into a HI. In this paper, the logistic regression (LR) technique is used for the health assessment of AC-powered SOVs using the selected features obtained from the previous step in Section 2.2.

The LR can be seen as a process with a two-fold objective: (i) fusing multiple features (independent variables) into a single value (*i.e.* HI) and (ii) restricting the HI between 0 and 1. The advantage of using the LR is that only data representing healthy and failure states are required to estimate the regression coefficients. Thus, the LR technique is suitable for problems with a limited number of historical data. As reported in the literature, the LR technique has been successfully applied to assess the health status of engineering systems based on extracted high dimensional features, for examples, see Yan and Lee (2005); Ompusunggu et al. (2012); Maulana et al. (2023).

Fig. 4 illustrates the steps to determine the HI by fusing a set of L selected features, represented by a vector $\mathbf{F} = [1 \quad F_1 \quad F_2 \quad \cdots \quad F_L]^T$. As seen in the figure, the selected features are fused by means of a linear combination using the LR model parameters $\boldsymbol{\beta} = [\beta_0 \quad \beta_1 \quad \beta_2 \quad \cdots \quad \beta_L]^T$ to compute the logarithm of "odds-of-success" $g(\mathbf{F})$ that is eventually transformed into the HI using a logistic function.

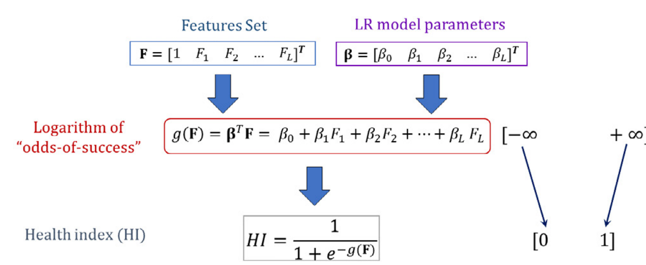


Fig. 4. Logistic Regression (LR) in a nutshell.

In the LR context, the model parameters $\boldsymbol{\beta}$ are identified using the maximum-likelihood estimator, aiming at finding a set of parameters for which the probability of the observed data is maximal, see Czepiel (accessed on April 2023). The parameter identification is conducted in an off-line fashion where two sets of features, $F_{healthy}$ and $F_{failure}$ representing healthy and failure states respectively, are used as a training dataset.

3. EXPERIMENT

A solenoid endurance test setup was developed to perform simultaneous ALTs on 48 AC-powered SOVs, as shown in Fig. 5. The type of used valves are direct acting 3/2 way *normally closed* (Burkert Type 6014). The ALTs were performed at an ambient temperature of 25 °C and attained by switching the valves on/off at a rate of 1 Hz for a total duration of approximately 6 weeks. Each valve is powered by an input AC voltage of 110 V at 50 Hz and supplied with compressed air at 8 bar in the inlet port.

(a) Test setup photograph

(b) Close up view of an air flow sensor

Fig. 5. Test setup for performing simultaneous ALT on 48 valves.

During the ALT campaign, both current and voltage signals were measured for each valve. Besides, the surface temperature and air flow rate of the SOV outlet just after the switch on/off were also measured for each valve as a means to have the "ground truth data" for labelling the end of life of each valve in an objective way. More details of the test campaign are described in Tod et al. (2023).

4. RESULTS AND DISCUSSION

The experimental data obtained from the ALT campaign discussed in Section 3 were analysed to compute all the 22 features described in Section 2.1. Since only 36 out of 48 valves actually reached the end of useful life during the ALTs, only of these 36 failed valves we extracted the features from the measurement data and evaluated the metrics described in Section 2.2. Figs. 6 - 9 show the calculated monotonicity, robustness, prognosability, and overall performance metric, respectively. The vertical dashed-line in the figures is a user-defined threshold that visually helps in selecting the most relevant features. For this case, a threshold of 0.9 was set.

In view of the monotonicity metric, only four features ($RZC1D1$, $ImFund$, $IdFund$, and $FCoulomb$) have a mean value higher than the threshold and exhibit small variations, as shown in Fig. 6. Regarding the robustness to outliers, most of the features are robust. 15 features have a mean value higher than the threshold and exhibit relatively small variations. However, in view of the prognosability, all the 22 features have the metric lower than the set threshold. From the overall performance metric, only the feature $FCoulomb$ is very close to the threshold as seen in Fig. 9. Nonetheless, the features $RZC1D1$, $ImFund$, and $IdFund$ are worth to be considered since

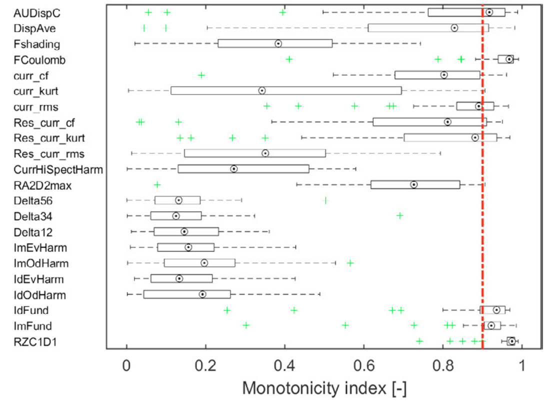


Fig. 6. Monotonicity index of all the calculated features

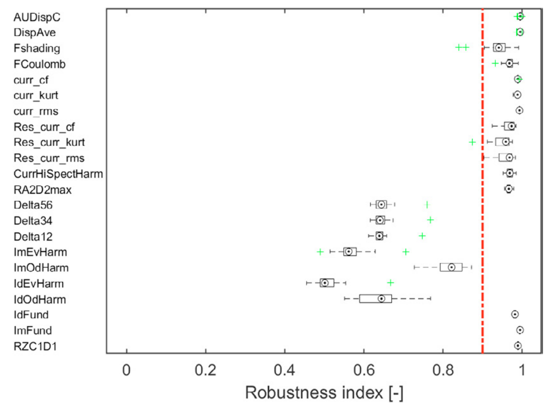


Fig. 7. Robustness index of all the calculated features

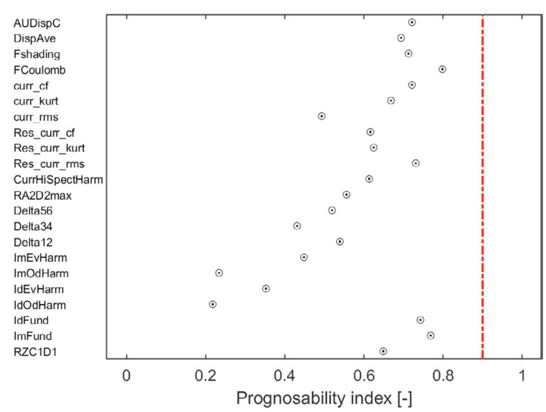


Fig. 8. Prognosability index of all the calculated features

the overall performance metric is above 0.8, which is still relatively high.

Notably, the feature $FCoulomb$ is more computationally expensive than the other three features $RZC1D1$, $ImFund$, and $IdFund$. Hence, when computational power is limited, the feature $FCoulomb$ might be less preferred. To further verify these findings, the top three features, namely $FCoulomb$, $ImFund$, $RZC1D1$, and the bottom one $IdOdHarm$ are plotted in Figs. 10 - 13, from the onset of the degradation to the end of useful life. It is clear from the figures that the top three features show very clear trends. As expected, the bottom feature does not show clear trends.

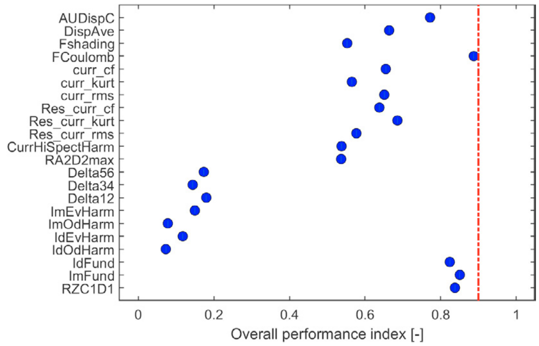


Fig. 9. Overall performance index of all the calculated features

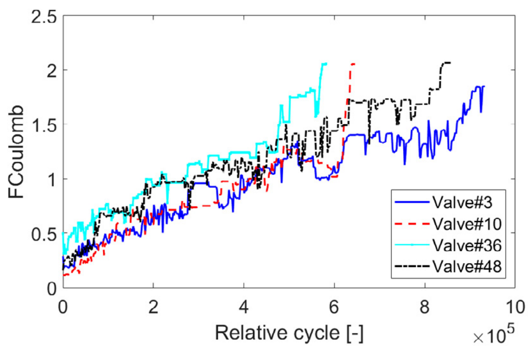


Fig. 10. The evolution of the feature $FCoulomb$ of several failed valves from the onset of degradation to the EOL.

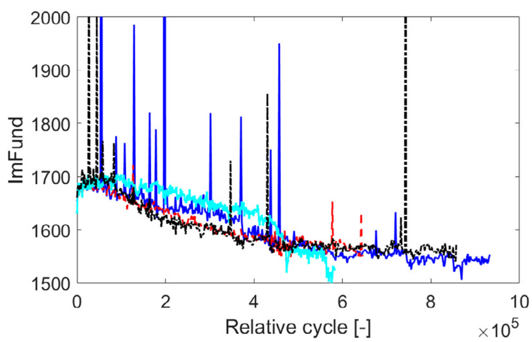


Fig. 11. The evolution of the feature $ImFund$ of several failed valves from the onset of degradation to the EOL.

Despite showing clear trends, the feature $ImFund$ still exhibits occasional outliers which require special attention when developing a prognostic algorithm using this feature. However, the variation of this feature value at the end-of-life is quite small which offers some advantages for prognostics. Furthermore, the variation of the feature $RZC1D1$ value at the end-of-life is quite large. This is demonstrated by a lower prognosability metric compared with the other top features, see Fig. 8. Hence, such large variation might need to be considered when developing a prognostic algorithm using this feature.

To demonstrate the health assessment of AC-powered SOVs using the LR technique, the two top features, $FCoulomb$ and $RZC1D1$, respectively shown in Fig. 10 and Fig. 12, are fused to model the health index. Note that one can also fuse the three top features or use single

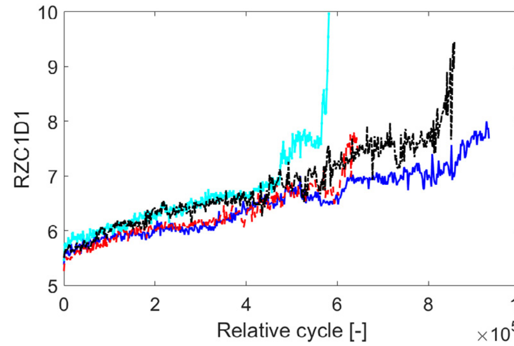


Fig. 12. The evolution of the feature $RZC1D1$ of several failed valves from the onset of degradation to the EOL.

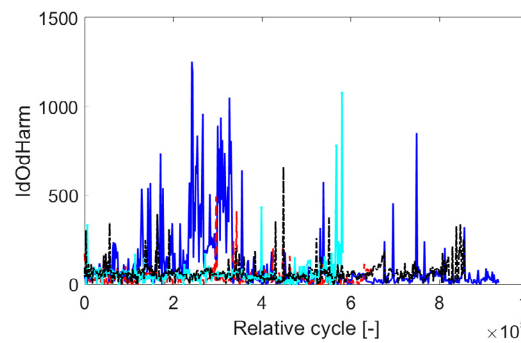


Fig. 13. The evolution of the feature $IdOdHarm$ of several failed valves.

feature to implement the health assessment using the LR technique. Figure 14 shows the health index (HI) estimated using the LR technique of several failed valves from the degradation onset to the EOL. It is seen in the figure that the estimated HI of the failed valves decreases from the value of around 1 to the value around 0 when reaching the EOL. This kind of representation is useful for non-experts / operators where they can easily monitor and interpret the health status of an AC-powered SOVs by looking at the HI.

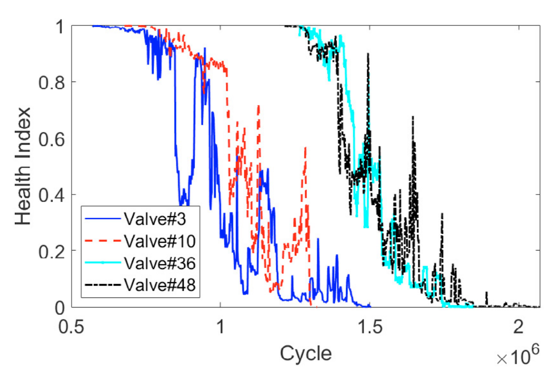


Fig. 14. The health index estimated using the LR technique of several failed valves.

5. CONCLUSION AND FUTURE WORK

Twenty-two prospective features for health monitoring and assessment of AC-powered solenoid operated valves

(SOVs) have been quantitatively evaluated using well-established prognostic feature metrics, namely monotonicity, robustness and prognosability. All these features are extracted from the electrical signals measured on 48 identical AC-powered SOVs, using three different methods, namely based on (i) a first-principle model, (ii) physics-inspired signal processing and (iii) statistical technique.

Based on the quantitative evaluation results, four features, namely $FCoulomb$, $IdFund$, $ImFund$, $RZC1D1$, are ranked high because the overall performance metric is higher than 0.8 (maximum range of 1). To demonstrate the proposed methodology, as an example, two top features, $FCoulomb$ and $RZC1D1$, are fused using the logistic regression (LR) model to predict a health index (HI) that ranges from 0 and 1. By transforming the fused features into the HI, non-experts / operators can easily monitor and interpret the health status of AC-powered SOVs.

Future work will be developing and evaluating some prospective algorithms for the remaining useful life (RUL) prediction of AC-powered SOVs.

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