TORQUE-BASED LIFE INDICATORS FOR GEARS IN VACUUM

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ABSTRACT

The in-orbit lifetime of spacecraft spur gear units is clearly limited by lubricant failure, which in vacuum is immediately followed by scuffing and subsequently severe wear of tooth faces. Such failure will result in a sharp increase in gear torque eroding margins or causing mechanism failure. This paper analyses torque data for solid, fluid and hybrid lubricated spur gears to determine which of a several frequently used frequency- and time-domain condition monitoring indicators can detect the onset of gear lubrication distress and imminent wear-out prior to an increase in gear torque. It is shown that, at least at test-rig level, some of the selected indicators can indeed provide an early detection of gear degradation as a result of lubricant failure. This observation raises the possibility that by extension from torque to motor current monitoring, such techniques may ultimately be used for in-situ monitoring of flight hardware.

INTRODUCTION

In contrast with in-air operation, where gear life is usually determined by the fatigue life of the gear materials, in a vacuum environment, the lifetime of a set of gear stages is defined by failure of the lubricant, which is immediately followed by scuffing and subsequently severe wear of tooth faces; phenomena which in turn increase mean and peak-to-peak gear torque losses. Whereas on orbit, lubricant failure may be detectable only as a rapid increase in motor current, in an experimental setting, torque indicators can be directly measured during low speed torque reversal sequences. Lifetime is defined at the point where mean or peak torque exceeds a threshold relative to its steady-state value (or results in an unacceptable actuator margin).

The above conditions pose a double challenge to the development of space mechanisms involving gears: a lack of understanding of the underlying mechanisms and a dearth of experimental data. To address this, three testing campaigns have been carried out [1] on ESTL's 4-square gear rig [2], where two identical gear stages are counter-loaded using a torsional spring (Fig.1).

The primary aim of the work in these campaigns was to characterise performance of various lubricant and material combinations in terms of expected friction and lifetime as a function of contact stress so as to produce a "catalogue" of spur gear performance of use to designers of space mechanisms. A secondary aim has been to investigate the hybrid lubrication behaviour previously reported in Pin-on-Disc (PoD) tests. However, the present, opportunistic study takes advantage of torque data from all test campaigns for some additional analysis, with a focus on the progression of the degradation process (from initial running-in, through steady state operation to ultimate wear-out) rather than the actual performance of the examined specimens. This parallel study therefore aims to advise on suitable means of processing gear (and perhaps ultimately even motor performance data) in order to definitively detect incipient lubricant degradation.

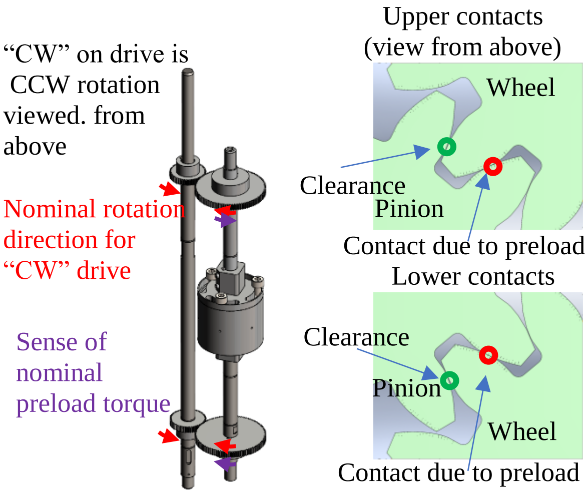

Figure 1. The 4-square counter-loading principle.

TEST CAMPAIGNS

Test conditions

All tests were performed under high vacuum on miniature spur gears of 0.5mm module, with 40 teeth on the pinion and 120 on the gear, for a gear ratio of 3. A matrix of test conditions for the tests used in this study follows (Table 1), where the conditions (speed, stress, temperature) are recorded, alongside the total duration of the test (expressed in terms relative to a lifetime assessed using mean torque) and the steady-state torque (T_{ss}). The gears were solid, fluid and hybrid lubricated (sputtered MoS_2, Braycote 601EF, and Braycote 601EF/MoS_2 respectively). Gear condition is given by a 3-digit code referring to gear precision (7=ISO-7; 5=ISO-5), gear material (4=17-4PH; 5=15-5PH steel) and surface treatment (H=H1025 hardening; P=plasma nitriding). The tests are ongoing, and the matrix is constantly being augmented.

Test	Lubn.	Gear condition	Peak Stress (GPa)	Speed (rpm)	Temperature (°C)	Test duration (rel. to Life)	T_{ss} (Nmm)
T101	MoS_2	7.4.H	0.425	250	22	513%	2.15
T11A	MoS_2	7.4.H	0.425	250	22	346%	2.15
T102	MoS_2	7.4.H	0.850	50	22	125%	6.51
T103	MoS_2	7.4.H	1.164	50	22	104%	15.17
T105	grease	7.4.H	1.164	100	22	101%	33.40
T106	hybrid	7.4.H	1.164	100	22	100%	42.30
T108	grease	7.4.H	0.425	100	22	148%	3.01
T109	hybrid	7.4.H	1.164	50	22	281%	29.30
T110	MoS_2	7.4.H	1.164	50	80	190%	14.50
T111	grease	7.4.H	1.164	100	80	187%	30.00
T112	MoS_2	7.4.H	0.425	100	80	195%	1.91
T323	grease	5.5.H	1.164	100	22	106%	48.29
T223	grease	5.4.H	1.164	100	22	115%	38.18
T221	grease	5.4.H	0.425	100	22	147%	7.52
T222	grease	5.4.H	0.850	100	22	120%	20.63
T322	grease	5.5.H	0.850	100	22	108%	24.65
T211	MoS_2	5.4.H	0.425	100	22	257%	3.69
T213	MoS_2	5.4.H	1.164	100	22	192%	19.90
T241	grease	5.4.N	0.425	100	22	194%	6.11

Table 1. Matrix of gear testing conditions.

Torque reversals at low speed (5rpm) were performed and the mean (T_m) and peak-to-peak (T_{pp}) torque were used as indicators for lubrication life. These two indicators are traditionally used in most tests at ESTL on various mechanisms and components, including bearings and gears. The tests were stopped initially when Tm, reached 125% of its steady-state value, a point recorded as the conventional lifetime, L, for the test. At that time, the vacuum chamber was opened and in most cases some evidence of metallic debris was detectable on the upper and lower pinion (debris sampled using a magnet). The chamber was then re-evacuated and the tests continued until Tm reached 200% of steady-state, with that interval being considered as the conventional wear-out duration. This occurred in most cases relatively quickly, with the torque curves having a characteristic hockey-stick shape.

Observed failure modes

Post-test inspections showed a similar pattern of wear on both pinion and gear surfaces. The wear pattern seemed to be independent of the lubricant used or any other test parameter except duration. Short tests showed only scuffing marks, while longer tests resulted in pitting and cracks.

As lubricant failure is the cause of wear, we expected to observe scuffing as the main wear mechanism and third-body abrasion as a secondary. It is postulated that the pitting pattern replaces an earlier pure scuffing pattern in cases where the test is continued for a relatively long period after either the torque increase or the debris are first detected. Scuffing is caused by loss of the lubricant's ability to maintain a low-friction interface. For Braycote, which is a PFPE grease, this is due to tribochemical degradation and for MoS_2, due to a combination of film wear and removal of the resulting lubricant debris from the contact zone [3]. Given the above, it is reasonable to assume that, since the physical effects are similar, the set of tests should display uniform behaviour.

CONDITION MONITORING TECHNIQUES

Various condition monitoring techniques were applied to high frequency torque data collected during torque reversal operations executed during the above-mentioned life test campaigns. The aim was to investigate which condition monitoring indicators showed the highest potential to detect the early onset of lubricant failure, ideally even prior to unambiguous time domain changes to torque data. The techniques used are briefly described below.

Frequency- and time- domain observation methods

Transforming a time-domain torque signal to the frequency domain is a common way of extracting qualitative information about the condition of a gearbox. This can be done in a few ways:

Waveform observation. Sometimes, a straightforward observation of the patterns appearing in the time-domain representation of the torque signal is the best way to detect failure. In Fig.3, a few damaged teeth on the gear produce a pattern of peaks repeating twice per reversal segment, i.e. every 3 pinion revolutions. Such patterns can be convoluted by having the torque from two stages added up as the measured signal and, quite significantly, by the speed not being constant. **Time-Synchronous Analysis** (TSA) and **Dynamic Time Warping** (DTW) are two techniques which have been applied, in order to improve the clarity of the torque waveform. In TSA, the signal provided by the revolutions counter is used to align and superimpose all periods of gear rotation and cancel out the noise [4]. In DTW, the zero-crossings of the signal itself are used to perform a time-adjustment of each consecutive period to the preceding ones [5]. For the present set of results, whereas waveform observation has been crucial in verifying the onset of failure, neither TSA nor DTW was found to provide any additional clarity. This is due to tooth surface degradation being fairly uniform around the gear teeth and not localised, as either as fatigue-related tooth pitting or breakage would be.

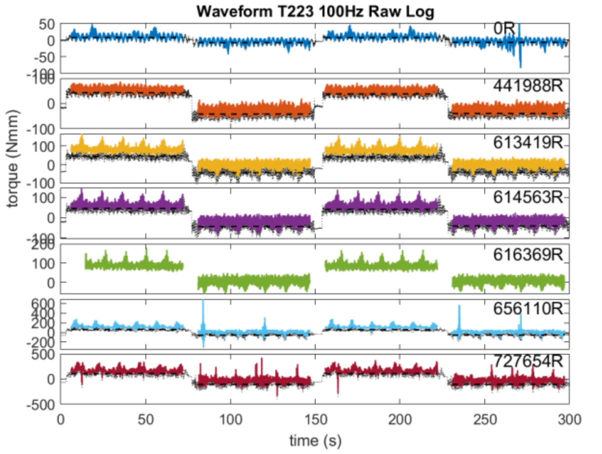

Figure 2. Snapshots of the evolution of waveforms of reversal torque as function of revolutions run from Zero to 727654 revs (reversals at 5rpm).

FFT with peak identification. This technique allows identification of whether observed peaks correspond to characteristic frequencies of the gears, or have other causes (e.g. bearing failure, shaft misalignment, motor malfunction). The gear-related frequency of most interest is the gear mesh frequency (GMF), the frequency at which two consecutive teeth come into contact. When there is failure at a specific tooth, sidebands appear around GMF and its harmonics, with a shift equal to a multiple of the pinion or the gear rotation frequency. More uniformly distributed tooth surface wear or pitting appears as broadband noise at higher frequencies. In Fig.3, such sidebands appear in the last 5 frames, around GMF (67Hz) and 2xGMF(133Hz).

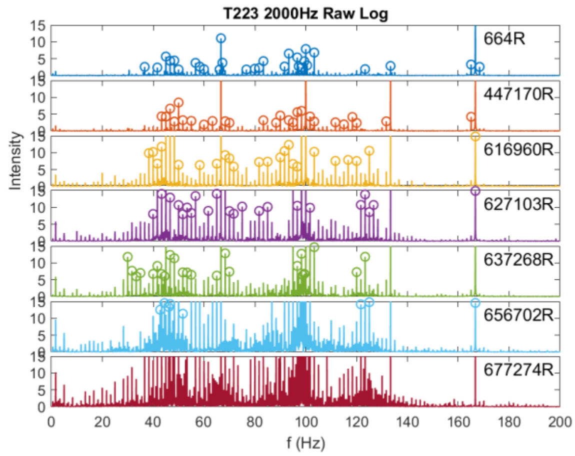

Figure 3. FFT snapshots of torque at running speed as function of revolutions from 664 to 677274 revolutions (running speed during measurement: 100rpm).

Spectrogram. In case of running at varying speeds, a spectrogram, which is a 2-dimensional representation of the signal in terms of both time and frequency (Fig. 4), was found useful in distinguishing the peaks (now represented by ridges) which are related to shaft speed. It also allows a clearer view of broadband noise. In the present case, it has proven to be the most practical method of determining the onset of failure, as reflected on Table 2.

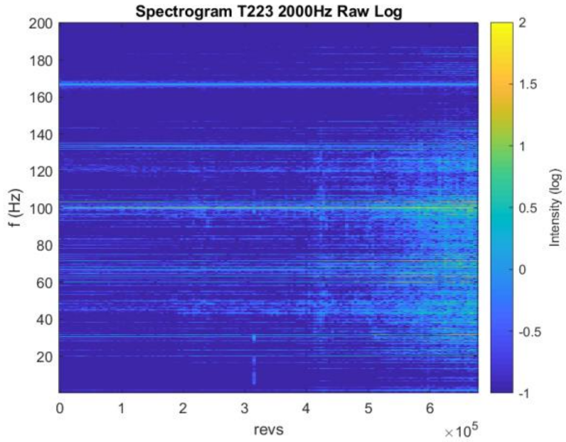

Figure 4. Spectrogram of torque at running speed.

Envelope Analysis using the Hilbert transformation. This technique has been claimed to be useful for enhancing and identifying peaks that are not identifiable with a regular FFT [6]. However, its application to our own data set failed to produce an improvement over FFT results, since the frequencies excited by scuffing gear failure were already the most prominent.

Noise-based indicators

The big drawback of the above-mentioned time- and frequency-domain methods is that they are difficult to employ in automated monitoring, since they either require human supervision or advanced pattern recognition to be able to distinguish the end-of-life conditions. On the other hand, noise-based indicators, applied either to a high frequency torque signal at nominal running speed, or to a low speed torque reversal signal, are produced as scalar time-series and are more applicable to conventional rules-based monitoring.

In our test campaign, two kinds of signal were available: a torque signal from low-speed (5rpm) torque reversals recorded at 100Hz for 120s; and a second torque signal from regular running (100rpm for most tests), recorded at 2kHz in 5s (Phase 1) or 25s (Phases 2 &3) segments. The following indicators were applied to both:

1. RMS, or the 2^{nd} spectral moment of the normalised and detrended torque signal. This represents the "general noisiness" of the system.

2. Kurtosis, or the 4^{th} spectral moment. This represents the "peakiness" of the noise. Since by definition the RMS torque features in the denominator of the Kurtosis parameter, all things being equal, these two indicators should be inversely correlated.

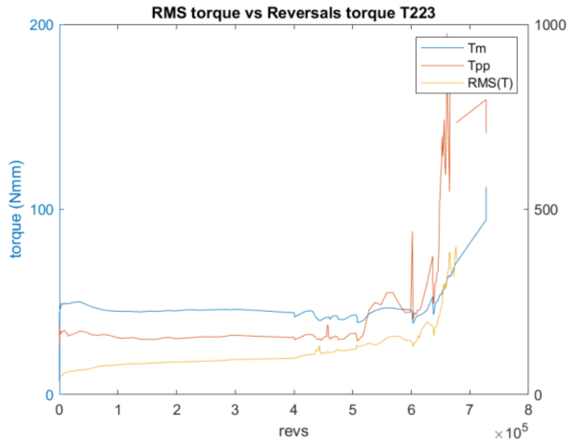

Figure 5. RMS torque during running (100rpm) vs mean and peak-peak torque during reversals (5rpm).

3. Permutation Entropy (PE). PE is one of a family of entropy measures that can be applied to a time-series: others are Sample Entropy (SE) and their multiscale counterparts (MPE and MSE). Such methods have been applied to time-series in finance, engineering and medicine, to look for patterns in stock prices, machinery and biological signals [7-8]. These all use the definition of entropy (the negative natural logarithm of a conditional probability) on top of a quantification of patterns in the time-series. In the case of PE, the probability of the emergence of ordinal patterns within a window of the time-series is used. PE was selected for this application because it provides information of similar quality at an efficient computational speed. In context of gear torque, it was found that PE decreases as wear progresses and is often inversely related to RMS.

In addition, the **temperature**, near each of the two gear stages was also recorded. A temperature increase beyond equilibrium reflects an increase in the power dissipated by friction (so failure/incipient failure). A temperature measurement proved to be the only means to distinguish which of the two gear sets may be failing first.

Correlations of indicators

Sometimes, when the trend of a single indicator will not provide useful information, the way a pair of them correlate in time might prove useful instead. These are quantified by running a windowed cross-correlation of two time-series. However, care must be taken to apply this technique only where it makes sense via a physical mechanism; otherwise there is a risk of inventing correlations without any causal relationship between them. In context of gear torque, three such correlations were examined:

1. Mean torque and temperature. This only applies to fluid lubrication. In theory, when EHL conditions prevail, the friction coefficient at the contacts is proportional to viscosity, which is inversely proportional to the temperature of the lubricant; therefore, an increase in temperature will decrease the running torque. When boundary lubrication prevails, the temperature stops affecting torque through viscosity. On the other hand, during the wear out phase, the dissipated frictional power is high enough to put the recorded temperature out of equilibrium: torque correlates linearly with temperature, with an ever-increasing coefficient, as wear progresses (Fig.6).

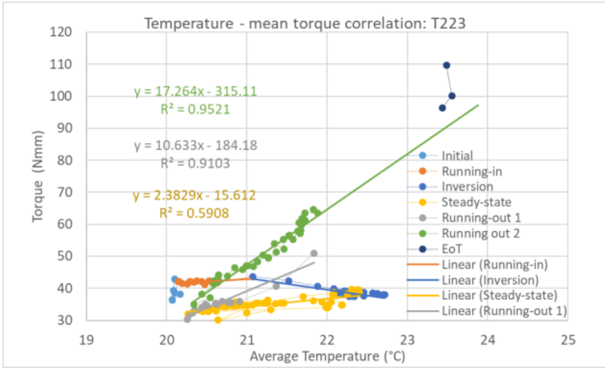

Figure 6. Piecewise linear regression of Tm and temperature.

2. RMS and kurtosis of torque. As explained above, in normal operation, a change in "noisiness" of torque should not affect its "peakiness". In wear-out, where scuffing is involved, the sharp peaks cause kurtosis to increase at a faster rate than RMS, so their correlation shifts from being highly negative to highly positive. This can be very prominent in some cases (as in Fig.7) and the reversal in correlation coefficient, can coincide with or even precede the individual indicators. Unfortunately, this does not occur consistently and dependably enough to provide a reliable indicator of incipient failure in all cases. It can however be used to monitor running-in, because the same mechanism is in effect as wear modifies the original surface of the gears.

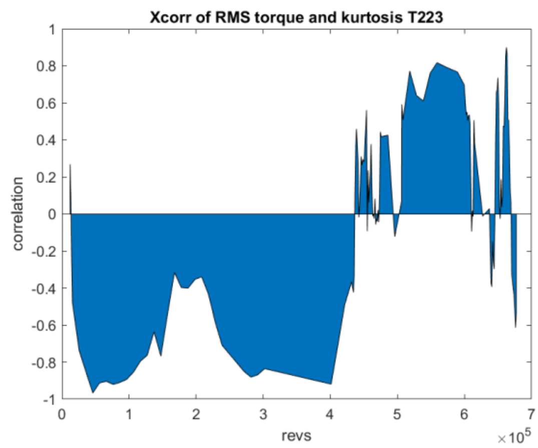

Figure 7. Cross-correlation of RMS and kurtosis, @100rpm.

3. RMS and PE of torque. PE provides a measure of repeatability of the noise patterns and increases with randomness. In normal operation, torque patterns are attributed to gear run-out and other geometrical imperfections and are somewhat ordinal. Wear breaks down those initial patterns because it is randomly distributed (increasing PE, e.g. in running in, as seen in Fig.8). Localised failure, as in most cases of wear-out, is expected to decrease PE by creating a regular pattern of "knocks", while RMS torque also increases. A noisier gear stage will thus coincide with a shift in PE, the direction of which depends on the type of degradation. In practice, as both types of degradation may coexist, the correlation coming out of the torque signal is not consistent.

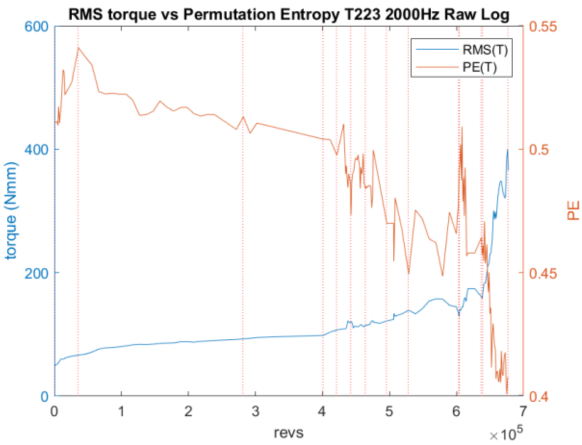

Figure 8. RMS and PE, @100rpm

PERFORMANCE QUANTIFICATION

For the purposes of the present study, all durations will be expressed in terms relative to L; in particular, the concepts of *relative life* (L_r) and of *remaining useful life* (RUL), are used:

$$RUL = 1 - L_r = 1 - \frac{revs}{L} \qquad (1)$$

thus for the test extension interval, where Tm is increasing between 125% and 200%, L_r>1 and RUL<0. A successful monitoring indicator should detect the onset of wear out before the conventional T_m trend monitoring does, at L_r<1 or RUL>0. The results of this procedure have been aggregated on Table 2, where they are compared to other ways to estimate the lifetime.

Statistical Process Control (SPC)

For a meaningful evaluation of the above-mentioned noise indicators, a way of extracting a measure of system life from each is required. For strictly quantitative indicators, such as the "classic" two, mean reversal torque and peak-to-peak reversal torque, which have a low variability during steady-state and are expected to rise sharply during wear-out, the procedure detailed above, involving thresholds at 125% and 200% of T_{ss}, is adequate. More nuanced indicators however may have a linear trend in steady-state and may deviate in any direction. A statistical process control (SPC) procedure, involving the moving average and moving standard deviation of observations over a specific window trailing the evolution of each indicator, is a more robust method. It can be summarised as follows (see also Figs.9 and 10):

1. Calculate a trailing moving average and moving standard deviation over 2 windows: a short term 5-point window and a long-term window with 20% of the series points.
2. For tests with few observations (<50), compare the time-series (blue) to the 5-point average (black), with a confidence interval (CI, dotted line) equal to 3x the standard deviation. Record the points outside this moving CI as alarm points (red circles).
3. For series with many observations, do the same comparing the short-term average (black) to the long-term average (green).
4. During a pre-set running-in period (5%-50% of total duration), do not record any alarm points.
5. Record the first alarm point as the indicator's lifetime (number of revs on chart).

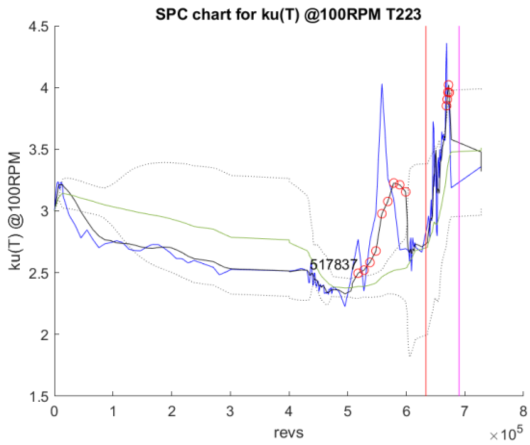

Figure 9. SPC chart of kurtosis @100rpm.

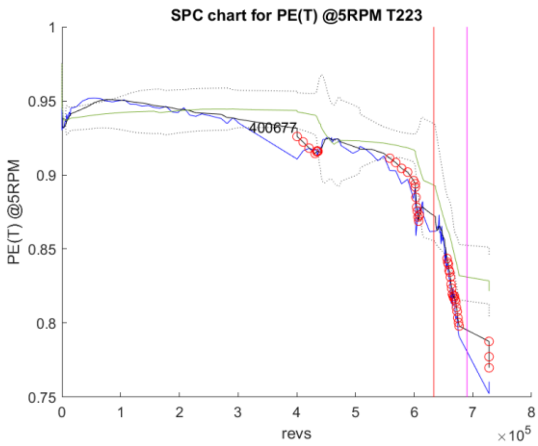

Figure 10. SPC chart of PE, @100rpm.

Combined indicators

It must be noted that sometimes, a single indicator may provide a false alarm in SPC processing, for statistical or technical reasons. A more robust way to treat SPC would therefore be to use combined (so-called "combo") indicators, where multiple indicators must provide an alarm at the same time. In Table 2, three combo indicators are evaluated: one combining all 8 available torque indicators (Mean, Peak-to-Peak, RMS, Kurtosis, and Permutation Entropy from low-speed reversal operations combined with RMS, Kurtosis and Permutation Entropy from higher speed (100rpm) running torque data) , a second combining the 5 indicators related to 5 rpm reversals only and a third one combining only the 3 indicators related to the 100rpm signal. In all cases, at least 2 indicators are needed to be in alarm to provide an alarm for the combo one.

Test	**Classic Indicators**		**Clustering Indicators**			**Visual Spectrogram**	**SPC Indicators**								**SPC Combo**		
							Reversals, 5rpm					**Running, 100rpm**					
	Tm 200%	**Tpp 125%**	**KMM**	**GMM**	**DPG**		**Tm**	**Tpp**	**rms**	**ku**	**PE**	**rms**	**ku**	**PE**	**2 from All Indicators**	**2 from 5 (5rpm)**	**2 from 3 (100rpm)**
T101	1.41	1.26	1.87	5.13	1.40	F	1.40	4.66	0.93	2.80	3.73	N/A	N/A	N/A	1.40	1.40	N/A
T11A	1.34	0.35	1.76	3.46	1.00	1.17	0.57	0.23	0.23	0.23	0.23	N/A	N/A	N/A	0.23	0.23	N/A
T102	1.25	13.02	0.80	1.25	1.05	F	0.60	0.20	0.95	0.45	0.20	N/A	N/A	N/A	0.20	0.20	N/A
T103	1.02	0.93	0.81	1.04	0.81	F	0.72	0.81	0.86	0.90	0.95	N/A	N/A	N/A	0.86	0.86	N/A
T105	1.11	0.91	0.97	0.80	0.96	0.90	0.52	0.53	0.51	0.64	0.56	0.51	0.60	0.88	0.51	0.52	0.63
T106	1.07	0.96	0.97	0.96	0.95	F	0.61	0.55	0.61	0.55	0.84	0.98	0.91	0.97	0.55	0.55	0.97
T108	1.45	1.21	1.18	1.21	1.09	1.21	0.99	0.75	0.74	0.74	0.74	0.75	0.74	0.74	0.74	0.74	0.74
T109	2.61	0.68	1.75	2.81	2.81	F	1.05	0.70	1.75	1.75	0.70	2.81	0.70	2.46	0.70	0.70	2.81
T110	1.67	1.90	1.55	1.90	1.55	F	0.86	1.90	1.90	0.35	0.35	0.35	0.86	1.90	0.35	0.35	1.90
T111	2.06	0.57	1.04	1.87	0.83	1.05	1.45	0.62	0.62	1.04	0.83	1.04	0.41	1.04	0.62	0.62	1.04
T112	1.31	1.12	1.39	1.40	1.40	F	0.84	1.39	1.12	1.12	0.84	0.93	1.39	1.58	0.84	0.84	1.49
T323	1.06	0.98	1.02	0.98	1.02	0.87	0.96	0.60	0.96	0.96	1.00	1.02	1.00	0.82	0.96	0.96	1.02
T223	1.09	0.86	1.02	1.02	1.04	0.82	0.93	0.83	0.65	0.69	0.63	0.65	0.82	0.83	0.65	0.65	0.83
T221	1.17	0.93	1.21	1.21	1.00	0.87	0.74	0.93	1.04	0.80	1.47	0.90	1.16	0.89	0.90	0.93	0.90
T222	1.20	0.89	1.12	1.12	1.12	0.81	0.97	0.91	0.62	0.82	0.88	0.62	0.62	0.62	0.62	0.88	0.62
T322	1.07	1.00	1.02	1.01	1.02	0.96	1.00	0.98	1.02	0.71	0.71	0.80	0.56	0.65	0.71	0.71	0.82
T211	1.46	1.54	1.39	2.57	1.40	1.52	2.57	1.66	1.26	1.26	1.26	1.13	1.13	1.79	1.13	1.26	1.13
T213	1.67	1.65	0.56	0.56	1.37	F	1.65	0.56	1.92	0.83	0.56	1.92	1.92	1.92	0.56	0.56	1.92
T241	1.86	1.00	1.01	1.92	1.01	0.97	1.78	1.79	1.78	1.94	1.72	1.84	1.92	1.94	1.78	1.78	1.94
MDN	**1.31**	**0.98**	**1.04**	**1.21**	**1.04**	**0.96**	**0.96**	**0.81**	**0.95**	**0.82**	**0.83**	**0.93**	**0.86**	**0.97**	**0.70**	**0.71**	**1.02**
Early		8	3	2	3	5	9	13	10	12	7	8	9	7	15	15	7
JIT		4	7	5	8	3	4	1	3	2	2	3	1	2	1	1	2
Late		4	5	4	6	3	5	1	4	3	2	2	2	1	3	3	1
Fail		3	4	8	2	8	1	4	2	2	8	2	3	5	0	0	5
Sum		*19*	*19*	*19*	*19*	*19*	*19*	*19*	*19*	*19*	*19*	*15*	*15*	*15*	*19*	*19*	*15*

Table 2. Torque based indicators compared in terms of relative life.
For each indicator set the Median (MDN) relative life is calculated and predictions are classified as "early" (<0.95), "just in time" (JIT, <1.05), "late" (>1.05), and "fail" (F, >T_m x200%).

Clustering

Clustering can be applied to the problem of state identification of the gear wear process, by making use of the parameter space which is produced from torque indicators. Unfortunately, this can only be used for verification and not predictive purposes, since the entire set of observations is required. The underlying concept, is this: if specific ranges of the indicators are for each test connected with a certain phase in the system's lifetime, then clustering of the observations should lead to clusters which are contiguous and discrete from each other, with little mixing, not only in the parameter space of the indicators where the clustering is performed, but also in the dimension of time (revolutions, relative life).

To test this, a method of clustering which can map to the three phases present in all life tests (running-in, steady-state, and wear-out), is required. If the number of clusters is predetermined, their size, in number of points should be variable; if the number of clusters is determined by a heuristic, that number should converge to 3 (unless the special conditions of the test do indicate more phases).

Three different methods of clustering have been applied:
1. K-means clustering (KMM) [9].
2. Gaussian Mixture Model (GMM) clustering with Variational Bayesian Inference [10-11].
3. Dirichlet Process Gaussian Mixture Model (DPG) [12].

The exact implementations are described in depth in the above references [9-12]. K-means has a predetermined number of clusters, while the two others are more advanced and use a heuristic which can vary the range of effect of the cluster, thus resulting in clusters with a very unequal number of points. Clustering has been applied to the set of 6 indicators (from both reversals at 5rpm and continuous running at 100rpm), excluding Permutation Entropy (PE). PE has been omitted because it was found to be confusing rather than helping the clustering. It is possible to use fewer indicators and still arrive at a good result.

The effect of clustering on the set of 6xN observations for T223 is presented in the form of a plot matrix in Fig.11. It is a symmetric matrix of plots of each indicator plus the number of revolutions for each observation (1st column), while histograms of each indicator are plotted on the diagonals. The conventional life for the test is represented by the dashed line. Clustering can indeed clearly distinguish between steady-state (coinciding with the cluster labelled "Phase 1") and wear-out (coinciding with "Phase 2") and locate the end-of life (here expressed in terms of L_r as defined above), at a point very close to the one given by the standard criterion or by SPC.

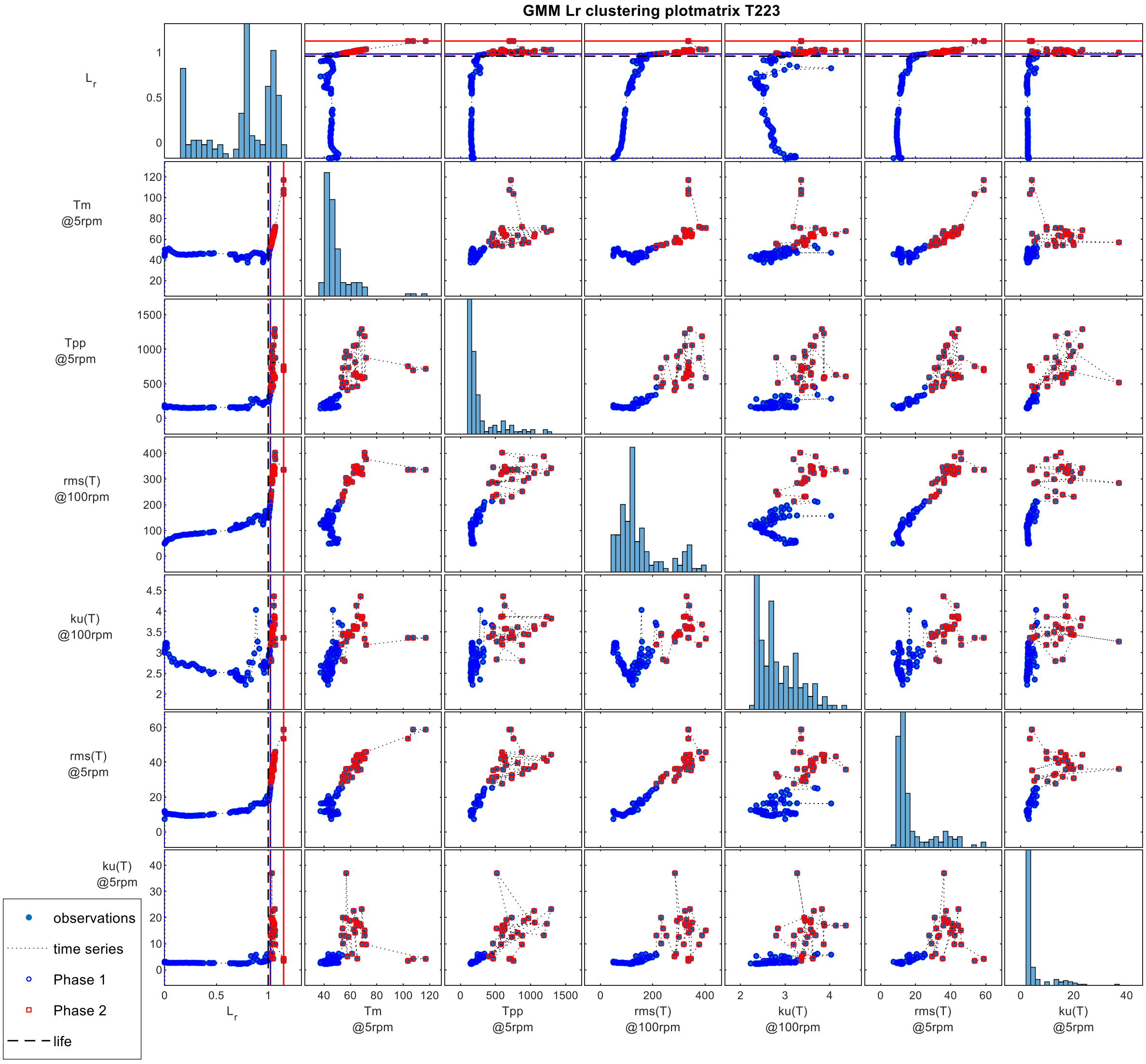

Figure 11. Use of GMM clustering to identify the onset of wear out, in terms of Relative Life.

Similar outcomes have been found for all tests; the clusters are generally discrete and contiguous and bad results are only given in 3 cases, namely in short tests where the number of observations is small, or when stops have affected the evolution of the indicators introducing sharp breaks, or, finally, when noisy running-in is involved, since it is possible to misinterpret it as being the same phase as wear-out.

The performance of the 3 clustering methods as lifetime indicators is summarised in Table 2. Overall, they are not as early as classic indicators or SPC, but if short tests are omitted, their performance is found to be similar. However, they agree well with the classic threshold, based on T_m. Comparing the 3 clustering methods, DPG is slightly better than GMM. KMM, although it may appear as good, enjoys results skewed by some random success in short tests. It remains an open question whether clustering can help determine regions of safe operation in the indicator parameter space, in absolute terms.

DISCUSSION

In Table 2, the detections of wear-out initiation achieved by all the above-mentioned methods are classified as “early”, “just-in-time”, “late” or “failed” based on how they fare compared to “T_m x125%”. A good performance would involve a low median detection point (<1) and as few failures to detect as possible. It can be concluded, that SPC provides a considerably earlier detection of wear-out compared to the classic indicators, especially if combo indicators are used. It is characteristic that both T_m and T_{pp} from 5rpm reversals, achieve significantly earlier detections if treated with the SPC procedure, rather than with the classic threshold. All visual inspection methods produce approximately the same detection lifetimes (with the Spectrogram being the most practical) but have many instances of failure to detect. Correlation may also be used as supporting evidence, since it helps link the indicator trends to processes of the physical system. Clustering, albeit not applicable to condition monitoring, but only to post-test analysis, is very useful in providing validation of the detections made by noise-based indicators.

CONCLUSIONS

It has been found that, depending on how gradual the wear-out process is, torque-based indicators can achieve an early detection of wear as a result of lubricant failure. For the specific problem posed by torque monitoring of gear stages subject to scuffing failure under vacuum, SPC indicators for Peak-to-Peak torque, Kurtosis and Permutation Entropy achieve the earliest detections with the fewer failures to detect, especially if they are combined. However, all tools should remain under consideration for applications, which may present different idiosyncrasies.

Especially if such monitoring can be extended from torque to motor current monitoring, these techniques may ultimately be used for in-situ monitoring of flight hardware. The opportunistic utilisation of data obtained from ESTL’s gear testing facility in campaigns aimed at lubricant lifetime and material performance has demonstrated that the facility can not only be used for the provision of lifetime data for space lubricants at the gear component level but also serve as a testbed and proving ground for such condition monitoring technology, and a means of supporting future diagnostic test developments.

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