N91-18975

1990

NASA/ASEE SUMMER FACULTY FELLOWSHIP PROGRAM

MARSHALL SPACE FLIGHT CENTER
THE UNIVERSITY OF ALABAMA

IS IT POSSIBLE TO IDENTIFY A TREND IN PROBLEM/FAILURE DATA ?

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Contract No.:	NGT-01-002-099 The University of Alabama

In many scientific endeavors, researchers want to determine whether a sequence of observations taken over time exhibits some type of trend. The NASA Standard, "Trend Analysis Techniques" (NASA-STD-8070.5), describes a variety of statistical methods that could be applied to time series data. Generally, trend is regarded as a smooth broad motion of the system over a "long" term. Several techniques are currently being used. The result of these efforts is reported in "Quarterly Problem Trending Report for MSFC Shuttle Elements and Payloads" prepared by the Calspan Corporation. However, the nature of the problem/failure data poses difficulty in identifying a trend.

One of the major obstacles in identifying and interpreting a trend is the small number of data points. Future trending reports will begin with 1983 data. As the problem/failure data is aggregated by year, there are just seven observations (1983-1989) for the 1990 reports. Any statistical inferences with a small amount of data will have a large degree of uncertainty. Consequently, a regression technique approach to identify a trend is limited. Though trend determination by failure mode may be unrealistic, the data may be explored for consistency or stability and the failure rate investigated. In what follows, various alternative data analysis procedures are briefly discussed. Techniques that could be used to explore problem/ failure data by failure mode. The data used is taken from Section One, Space Shuttle Main Engine, of the Calspan Quarterly Report dated April 2, 1990.

There were four set of observations in the Quarterly Report SSME Section that had a statistically significant downward trend based on a regression analysis. There were a total of 36 data sets trended in the SSME Section. These significant trends were based on data from 1979 through 1989. Reconsidering these sets of data from 1983 on, not one of them has a significant regression fit at the .01 level, which is the level used in the Quarterly Report. If we begin with data in 1983, a significant downward trend at the .01 level of significance requires a Pearson product moment correlation coefficient of $r= -.875$, that is $r^2 = .765$. In addition to the Pearson correlation coefficient with the corresponding test of hypothesis based on the normal distribution, there are numerous nonparametric measures of association. Two widely used ones in connection with regression and trending are Spearman's rank correlation coefficient and Kendall's tau. These two procedures use the rank order of the observations rather than the actual observed value. The four sets of data that were previously fit with a regression model are summarized below with the data beginning in 1983.

Correlations and Observed Significance Levels

	Pearson	Spearman	Kendall
Fuel preburner injector			
erosion/wear	-.618(linear) p=.139	-.607 p=.137	-.429 p=.177
dents/etc	-.765(power) p=.047	-.857 p=.036	-.714 p=.024
contamination	-.675(linear) p=.096	-.685 p=.094	-.488 p=.111
Controller hardware			
unexplained anomalies	-.805(linear) p=.029	-.786 p=.054	-.714 p=.024

Another approach to exploring the data is from the perspective of consistency. That is, does the failure rate fluctuate from year to year or is it relatively stable? While this approach is not to identify a trend it may provide the experimenter with insight into the failure process. Assuming a Poisson model for the number of failures, a chi-square goodness of fit test, assuming a constant failure rate from 1983-1989, a Kolmogorov-Smirnov goodness of fit test with the same assumption, or a level of performance chart could be applied.

The chi-square goodness of fit test utilizes an assumed probability model and estimates the expected number of failures per year and then compares the observed number of failures with these expected frequencies. To specify the procedure, let X_i be the number of failures in year i and let t_i be the number of test seconds (or test starts) in year i. The expected number of failures, under the assumption of a constant failure rate, for year i is given by $\mu_i = \theta t_i$, where θ is the probability of a failure in a small interval. The constant failure rate estimate of θ is given by $\hat{\theta} = \Sigma X_i/\Sigma t_i$, where the summation ranges through the years 1983 to 1989. The chi-square test statistic is given by $T = \Sigma(X_i-\hat{\mu}_i)^2/\hat{\mu}_i$ which is approximately distributed as a chi-square random variable with 5 degrees of freedom. The table below displays observed and expected frequencies for the 3 fuel preburner injector failure modes plus 2 other randomly selected data sets.

The .01 critical value for a chi-square distribution with 5 degrees of freedom is 15.1. The value of the test statistic T gives some idea of the agreement between the observed results and the assumption of a constant failure rate. The value of T must be cautiously viewed in cases of small expected frequencies. Consult the reference by Lawal and Upton for this consideration.

Observed and Expected Frequencies

	83	84	85	86	87	88	89
Fuel preburner injector erosion/wear	3	4	5	1	2	4	3
	2.73	2.52	3.83	1.21	3.95	4.30	3.5
						T=2.33	
dents/etc	13	3	7	1	1	3	2
	3.72	3.44	5.23	1.65	5.39	5.86	4.7
						T=30.60	
contamination	3	5	4	0	1	0	2
	1.86	1.72	2.61	.82	2.70	2.93	2.4
						T=12.57	
LPOTP contamination	6	10	2	3	15	13	3
	6.45	5.96	9.06	2.85	9.35	10.2	8.2
						T=15.76	
HPOTP turbine nozzle second stage crack	1	1	1	1	0	7	2
	1.61	1.49	2.27	.71	2.34	2.54	2.0
						T=11.39	

Another technique to explore the stability of the failure rate is a level of performance chart. It is constructed and used as a control chart. Using the Poisson probability model, the overall failure rate estimate $\hat{\theta}$ is used to compute limits of $\hat{\theta} + 3\sqrt{\hat{\theta}} / \Sigma\, t_i$. The yearly failure rate estimates $\hat{\theta}_i$ are then compared, often graphically, with these limits. Values of $\hat{\theta}_i$ outside the limits point to extreme fluctuation of the failure rates. The table below gives the yearly estimates of θ with limits based on the pooled estimate for 3 of the failure modes previously considered.

Estimates of θ by Year (x 10^{-3})

	83	84	85	86	87	88	89	Limits
Fuel preburner injector erosion/wear	.10	.15	.12	.08	.05	.09	.08	(.03,.16)
dents/etc	.45	.11	.17	.08	.02	.07	.05	(.06,.20)
HPOTP turbine nozzle second stage crack	.03	.04	.02	.08	0	.15	.05	(.01,.10)

An alternative process control technique that would monitor the yearly failure rate relative to a specified target failure rate is a cumulative sum (CUSUM) procedure. The CUSUM procedure is a sequence of Wald sequential probability ratio tests used to detect a change in the distribution of the number of problems. As before, a Poisson distribution for the number of problems is used. The CUSUM procedure is often enhanced by a fast initial response (FIR) feature. The reference by Lucas discusses a Poisson CUSUM procedure.

A cumulative sum procedure cumulates the difference between an observed value Y_i, some normalized value of X_i, and reference value k. If this cumulation equals or exceeds the decision value h, then conclude the failure rate for that year is greater than the target rate. To detect an increase in counts, the CUSUM statistic is $S_i = \max(0, Y_i - k + S_{i-1})$. The FIR CUSUM typically uses a starting value $S_0 = h/2$. The CUSUM is restarted after indicating an out of target value.

CUSUM procedures are evaluated by calculating their average run length (ARL). The ARL should be large when the failure rate is at the target level and short when the rate is at an undesireable level.

The parameter k is the reference value for the CUSUM. Its value will be chosen to be between the acceptable failure rate (μ_a) and an unacceptable level (μ_d) that is to be detected. Although the desired level of μ_a is zero, it is usually not used since any occurence of a failure will then give a signal. The reference value for the Poisson CUSUM should be selected to be close to $k = (\mu_d - \mu_a)/(\ln \mu_d - \ln \mu_a)$.

After k is selected, the decision value h is chosen using a table look-up procedure. There are tables given in the article by Lucas. The value of h should give an appropriately large ARL when the failure rate is on target and an appropriately small ARL value when the rate is too high.

Use of a CUSUM takes more involvement from the analyst than do the goodness of fit test or the level of performance chart. The CUSUM, however, combines looking at the data for stability and checking agreement with a target value. A CUSUM procedure with an acceptable failure rate of 1 per 50,000 seconds and an unacceptable rate of 1 per 20,000 seconds has been applied to the problem/failure data. When a CUSUM value exceeds h then it is restarted with next data value. The results are comparable to those from the goodness of fit test and rate performance chart. Along with the chi-square goodness of fit test and the level of performance chart, even though simple, these techniques offer some insight to supplement the regression approach.

Trend fitting and trend estimation are very far, particularly with small samples, from being a purely mechanial process. There is great scope, even necessity, for personal judgement. Exploring the data for patterns can be a very difficult, delicate issue.

REFERENCES

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