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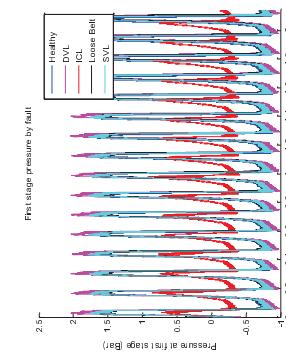
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# Distributional Considerations in Inference based Condition Monitoring Stages: Detection, Diagnosis, Prognosis.

## Abstract

The major focus of **condition monitoring (CM)** is in its prognostic and fault prediction abilities, the power of which is determined by selecting appropriate analytical techniques. Making the correct distributional and theoretical assumptions is the key to model robustness and strength of inference. Likewise a condition based rather than time interval based maintenance regime ensures near optimal performance for the duration of process operation,



**Figure 1** Variable profiling, first stage pressure measurements by fault (load 100).



**Figure 2** Distributional characteristics of first stage pressure measurements by fault (load 100).

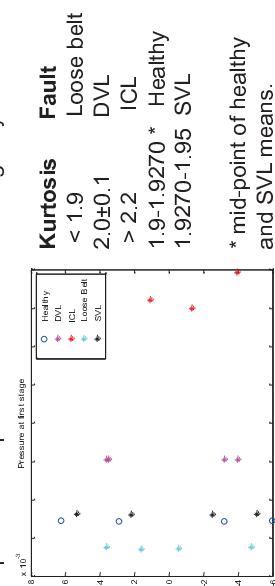
Distributions exhibiting severe negative skew may be represented by the **Beta** distribution with suitable shape parameters  $p$  and  $q$  and upper and lower data bounds  $a$  and  $b$  or by **Extreme Value Distributions**.

Positively skewed:  
Lognormal, Gamma or Weibull distributions;  
Exponential in extreme cases exhibiting positive outliers only.

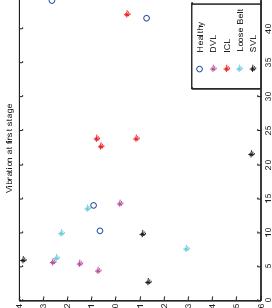
## 2. Diagnosis.

Having detected a deviation from the norm during operation accurate diagnosis of the source is critical. The more timely and precise the diagnosis of a fault, the greater the opportunity for planned maintenance potentially reducing the impact of disruption due to need for emergency intervention.

Identifying faults or deviant behaviour through variable profiling. Figures 1 and 2 show ICL to exhibit very different characteristics to the other fault cases.



**Figure 3** Scatter plot to show the Mean and Kurtosis of first stage pressure per number segment, load 100



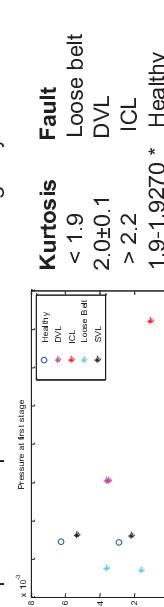
**Figure 4** Scatter plot of mean and kurtosis for the first stage vibration measurements per number segment with load 100

## 3. Prognosis

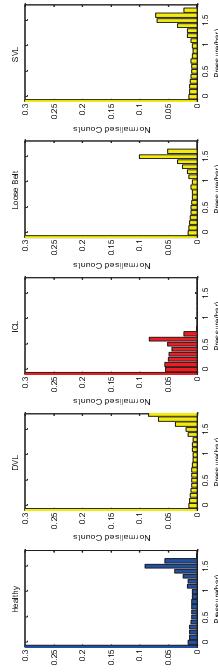
The ultimate skill of the condition monitoring process is the ability to make evidence based predictions of future behaviour based on current and past performance. Multivariate statistical analyses of historical data through monitoring deviations from expected or normal operating conditions or target values is utilised in the construction and assessment of prognostic modelling.

## Data distributions.

Can you estimate outcome and probability?  
Yes → Is the data symmetric or asymmetric?  
Yes → Is the data symmetric or asymmetric?  
No → Are the others clustered around a mean?  
Yes → Are the others clustered around a mean?  
No → Are the others clustered around a median?  
Yes → Are the others clustered around a mode?  
No → Are the others clustered around a mid-point?  
Yes → Are the others clustered around a mid-point?  
No → Are the others clustered around a mid-point?



**Figure 5** Typical data distributions in theory allow use of just a few parameters to model data.  
Source: [http://pages.stern.nyu.edu/~adamodar/New\\_Home\\_Page/StatFile/statdistns.htm](http://pages.stern.nyu.edu/~adamodar/New_Home_Page/StatFile/statdistns.htm) on 13-09-2013.



**Figure 6** In reality data distributions are complex and require more detailed exploratory investigations to establish suitable models.

## Summary and future work.

Whilst partitioning the data by number segment and clustering Segment means and kurtosis proved effective in determining an elementary rule for assigning to fault case through examining the first stage pressure measurements this was ineffective in the case of the vibration methods and would not be robust should a sequence of faults develop. On the other hand clustering algorithms based on the raw data would, if computationally possible, put too great a burden on resources. Future work is to focus on identifying the distributional characteristics of the data , estimation of distribution parameters (location, scale and shape ), multivariate modelling and subsequent sensitivity analysis.