Dynamic Outlier Algorithm Selection for Quality Improvement and Test Program Optimization

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TEST ADVANTAGE™
SOFTWARE

Purpose

- Outliers and quality improvement
- Outliers and test program optimization
- Outlier detection challenges
- Automated outlier detection

Outliers and Quality Improvement

- Early Life Failures
  - Good when tested
  - Fail in application
- Existing solutions are not economic for all products
  - Burn In
  - Lot Acceptance Testing

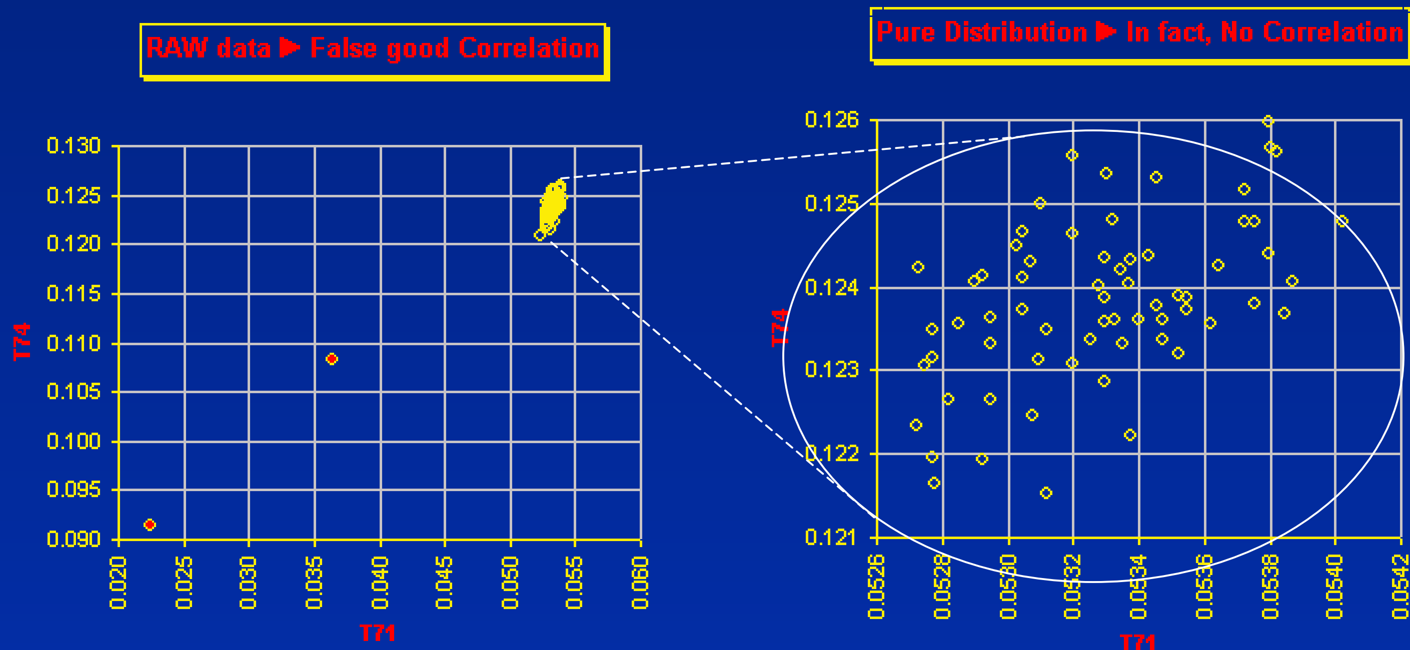
Outliers and Quality Improvement

- Established relationship between Burn-In failures/ELFs and abnormal devices in the 'Bin 1' population[1,2,3]
- Quality is inversely proportional to variance
  - Reduced variation improves quality
  - Eliminating parametric outliers from the Bin 1 population will reduce the number of early life failures

Test Program Optimization

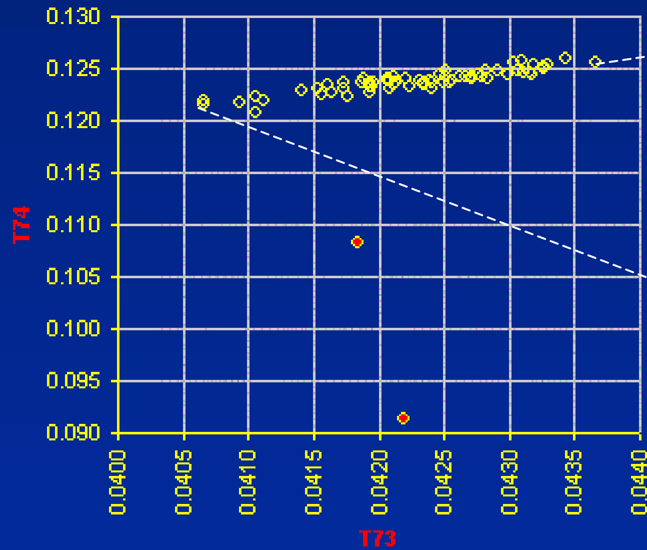
Throughput improvement – test removal

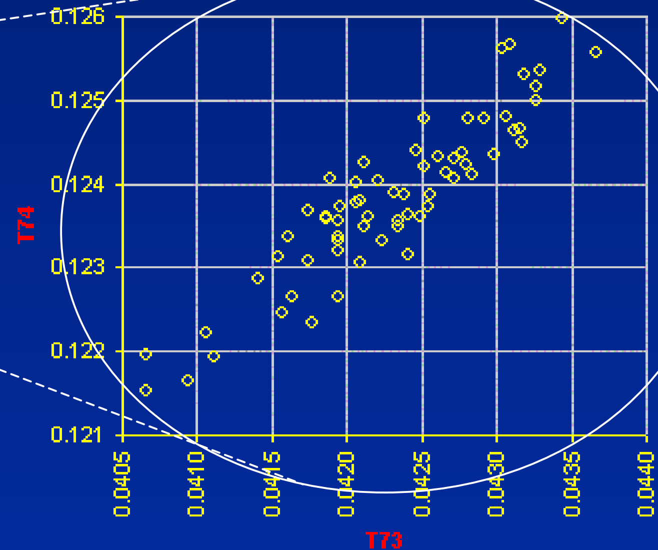
- High capability
- No failures
- No Alarms
- Correlated with other test(s)



False correlation

Test Program Optimization

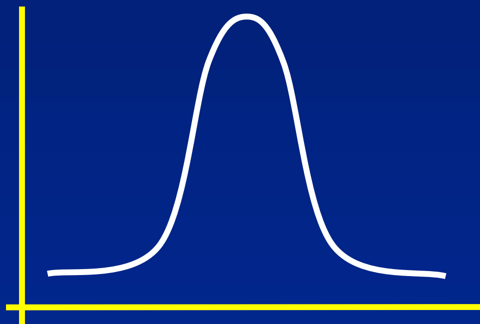




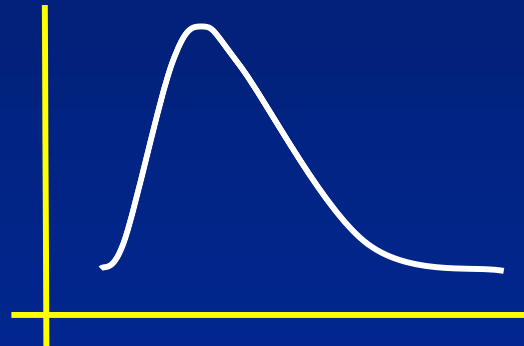
Missed correlation

Outlier Detection Challenges

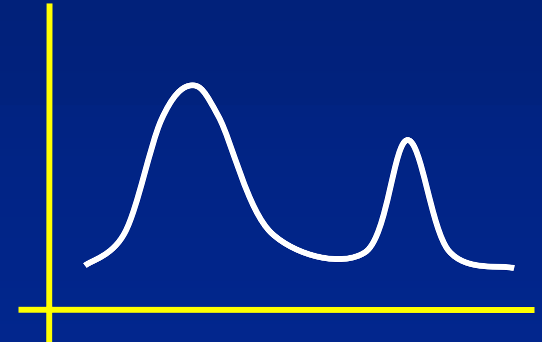
Data Populations



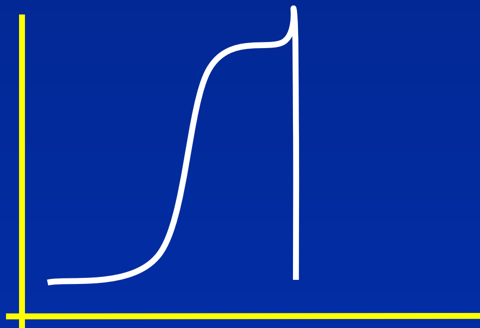
Gaussian



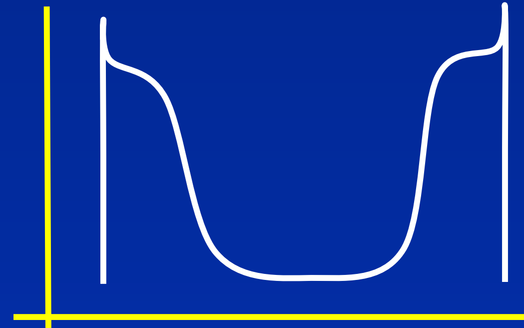
Log Normal



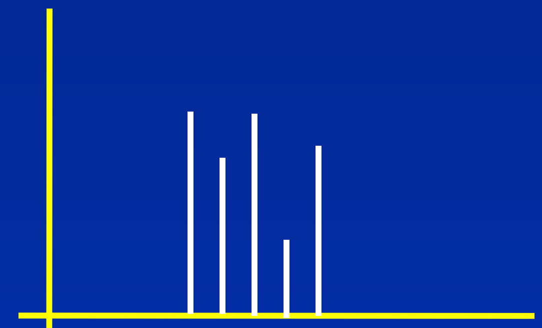
Bi-Modal



Clamped



Double-Clamped



Categorical

Outlier Detection Challenges

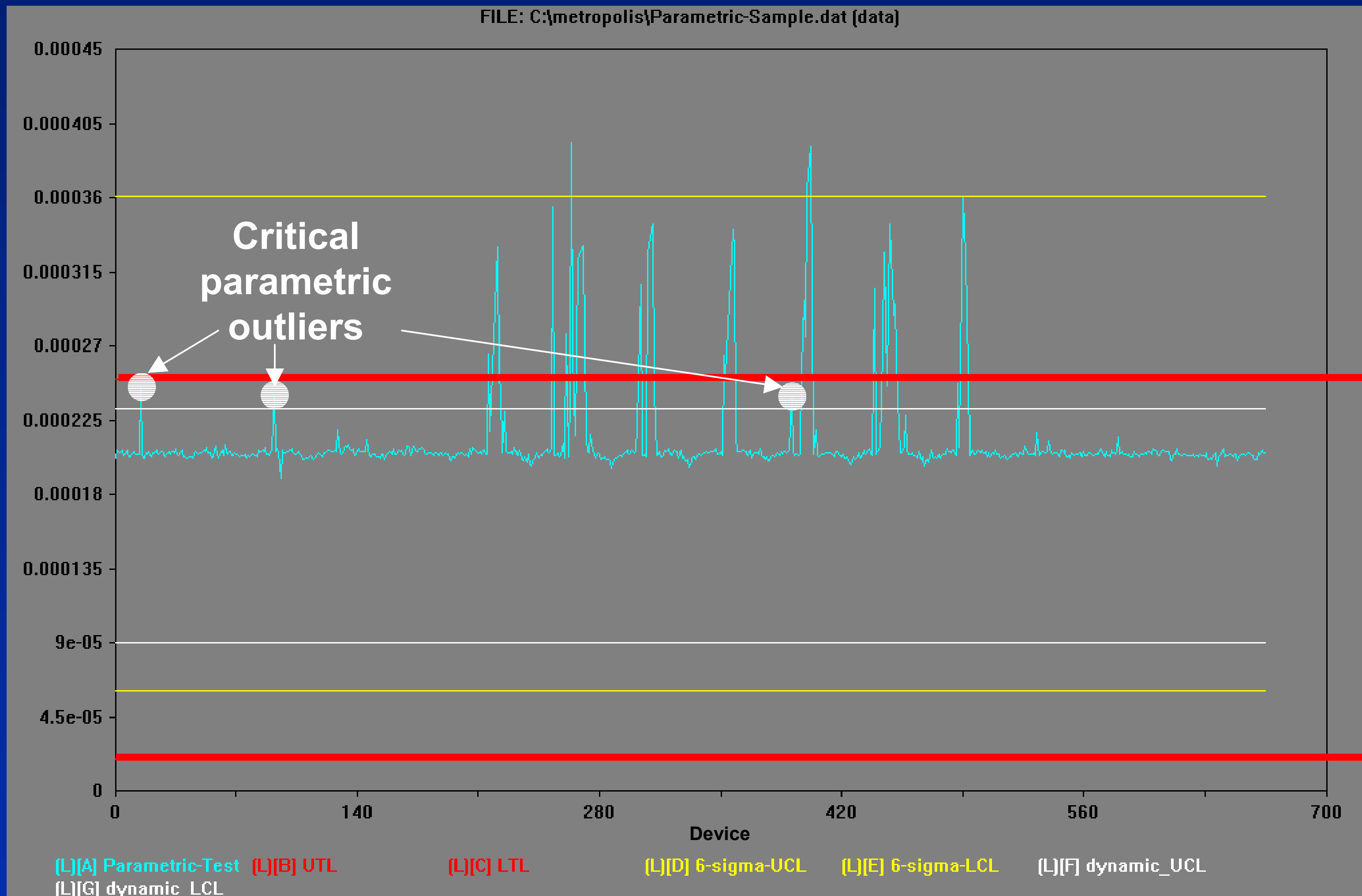
- Each data population will have distinct statistical characteristics
  - Mean, sigma
  - Range, number of unique values
  - Median, Inter-Quartile Range
- The presence (or absence) of test limits will also affect statistical relationships
  - Cp
  - Cpk

Outlier Detection Challenges

- Assuming a Gaussian distribution
  - Use: mean ± 6 sigma
- Alternatively, Percentiles provide a more 'robust' description of a data set, median and robust sigma (IQR/1.35)
- Other methodologies are available including proprietary algorithms that dynamically classify outliers based on their proximity to the test limits

Outlier Detection Challenges

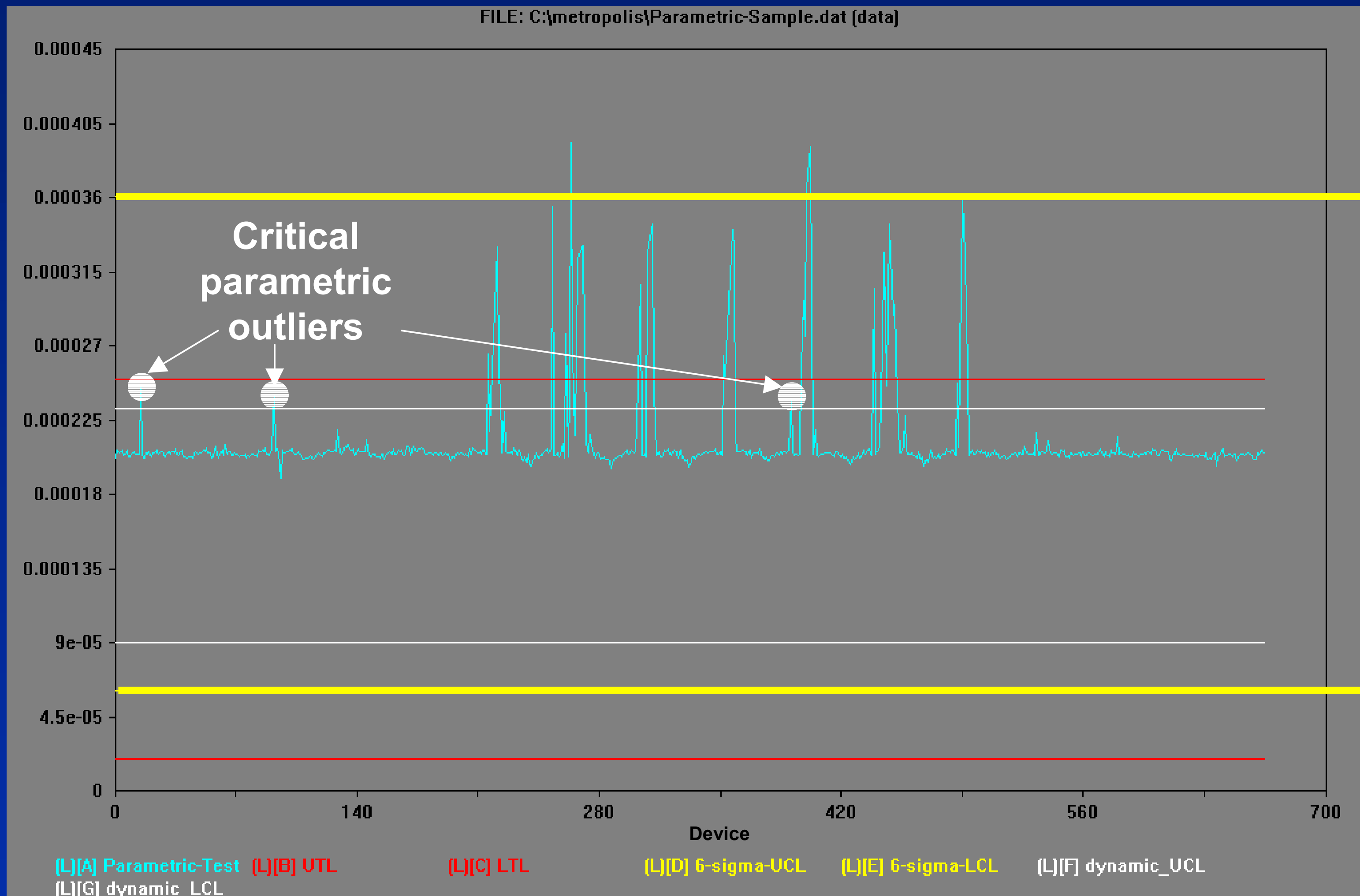
Example 1



Test Limits

Outlier Detection Challenges

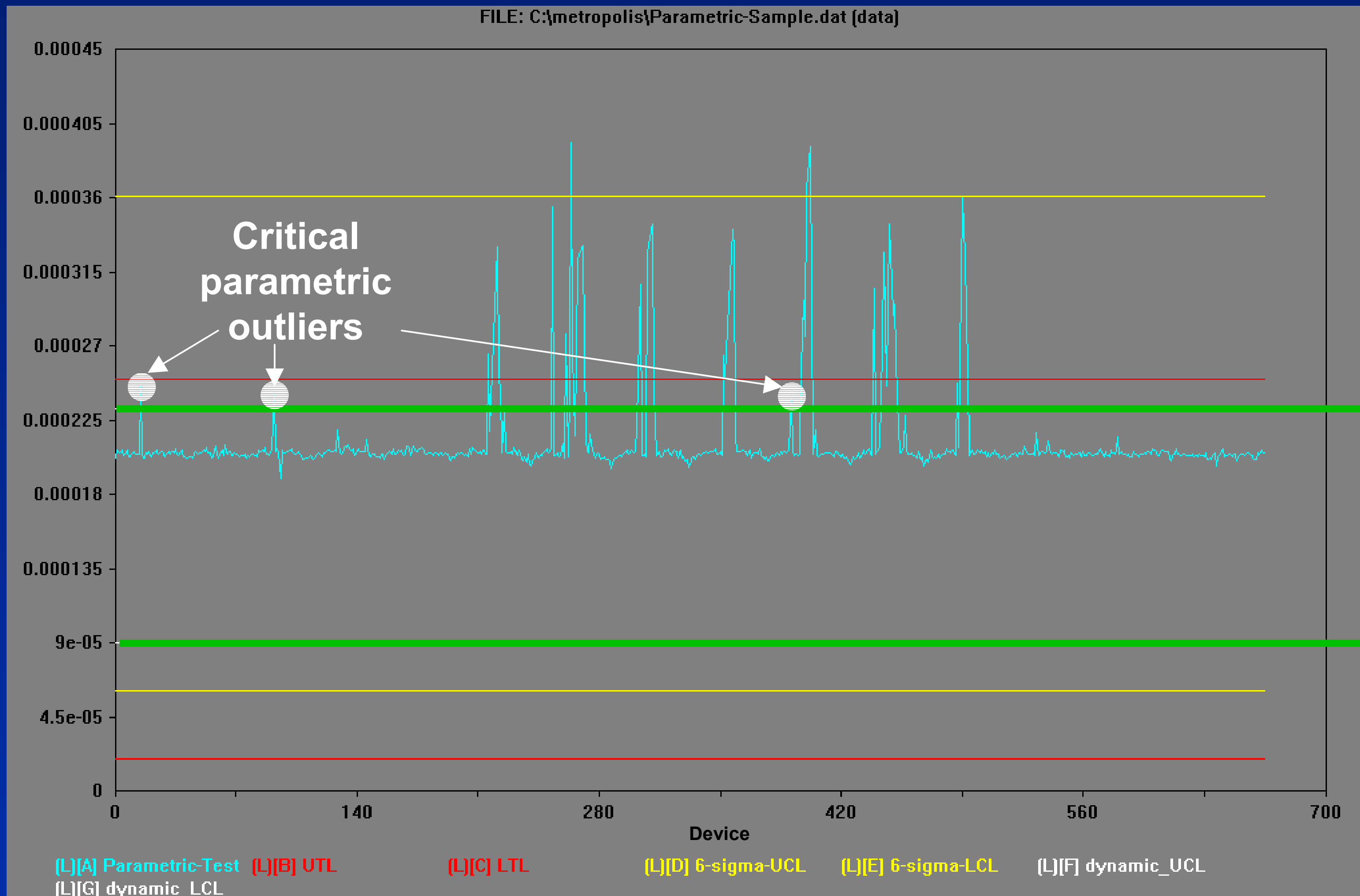
Example 1



Mean $\pm$ 6 sigma control limits

Outlier Detection Challenges

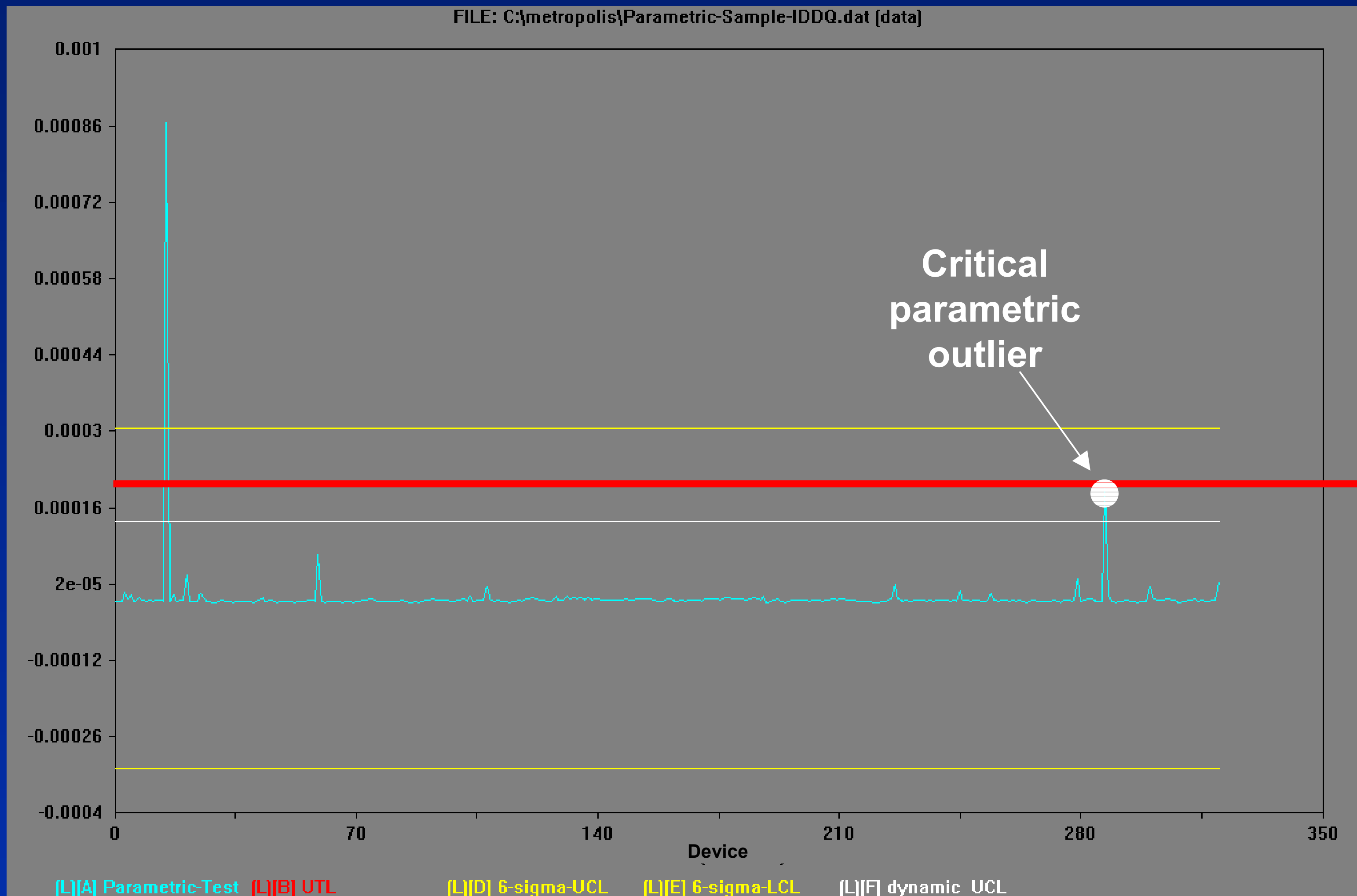
Example 1



dynamic control limits

Outlier Detection Challenges

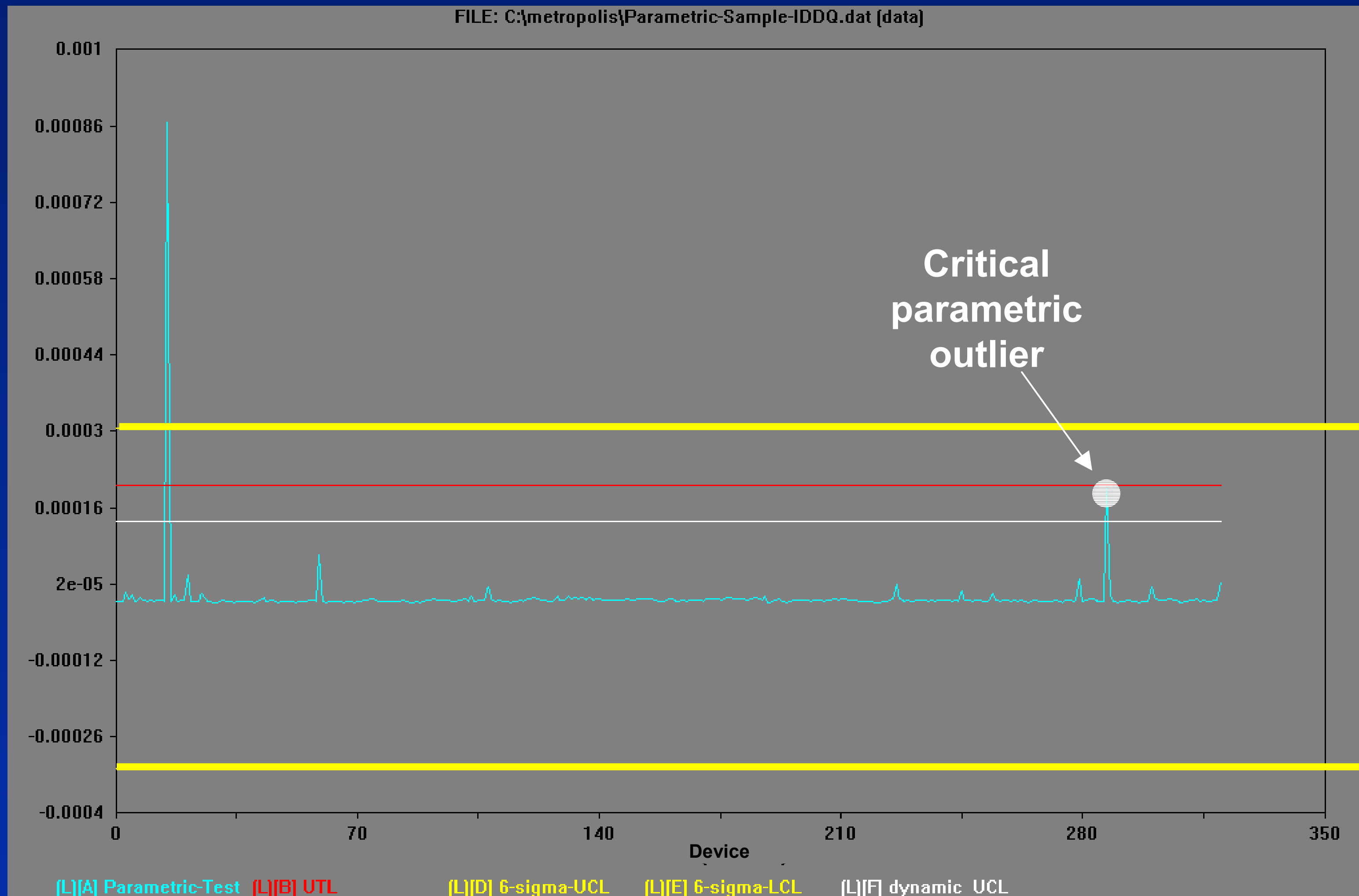
Example 2



Test Limit

Outlier Detection Challenges

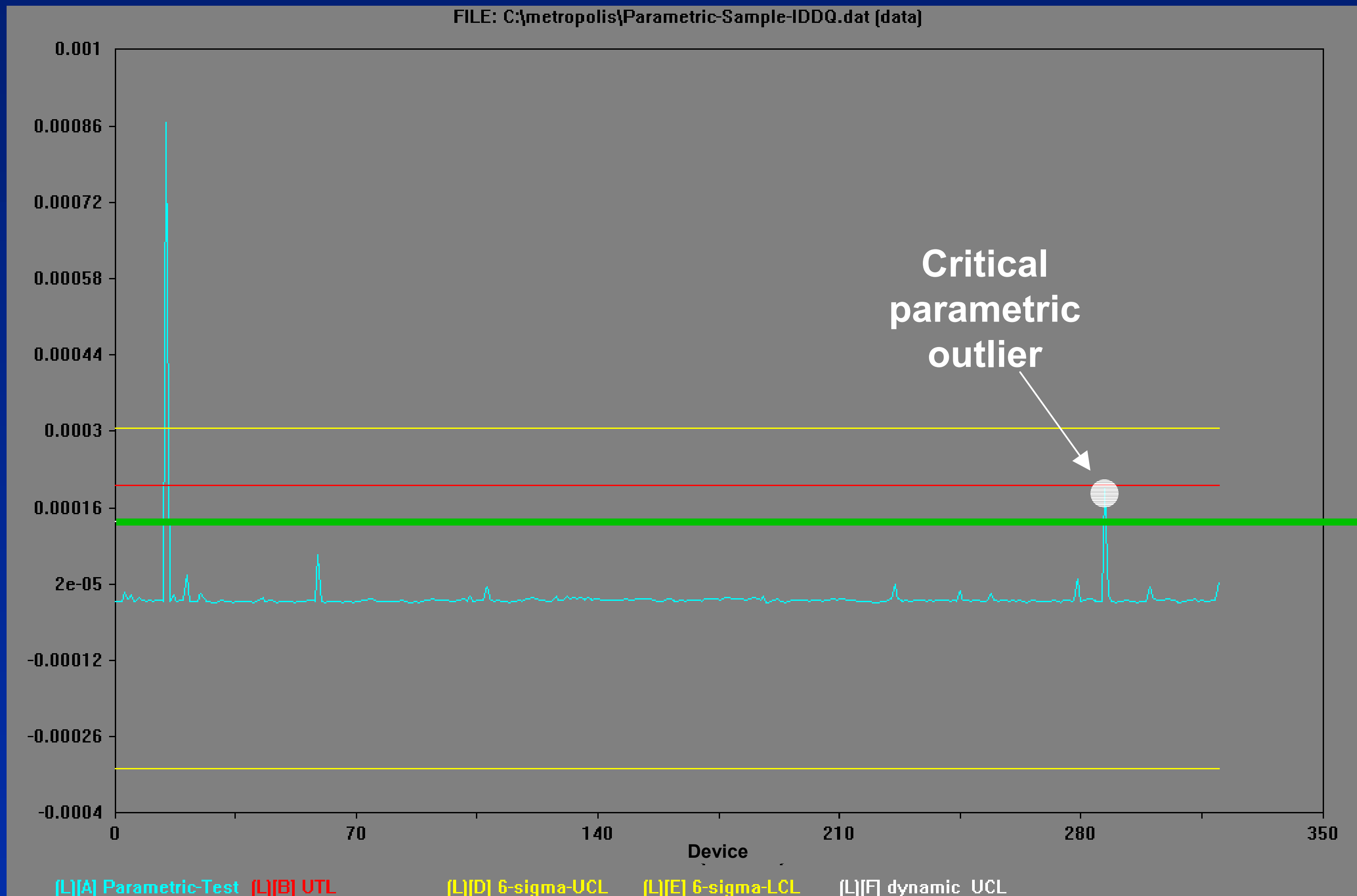
Example 2



Mean ± 6 sigma control limits

Outlier Detection Challenges

Example 2

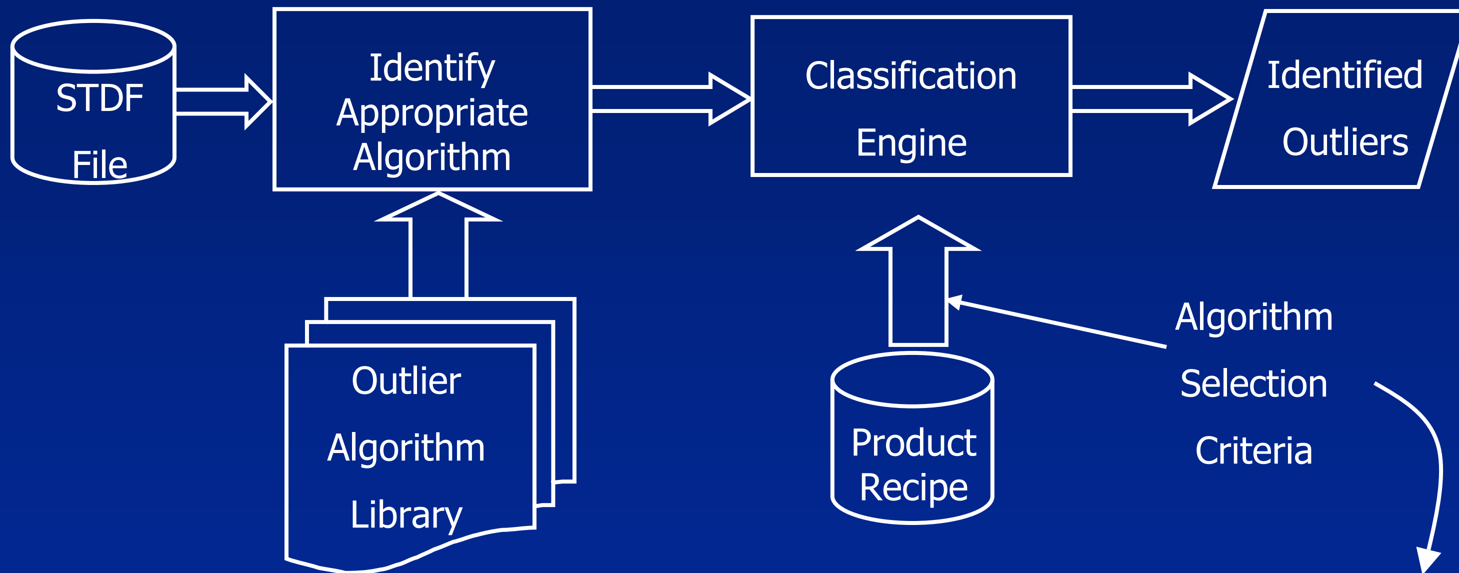


dynamic control limit

Outlier Detection Challenges

- Analysis of historical test data can be used to determine the most appropriate algorithm to use
- In practice wafer to wafer or lot to lot variation can cause test data distributions to change, invalidating pre-defined algorithm selection

Practical Outlier Detection System



- IQR (inter quartile range) normal distribution
- IQR log normal distribution
- mean ± N sigma
- median ± N robust sigma (IQR/1.35)
- Proprietary Algorithms
- Custom Algorithm, Chauvenet's criteria

Sample recipe rules (applied to each test):

- If CPK < N then use IQR normal …
- If RANGE/(UQT-LQT) < N then use proprietary
- If COUNT < 50 then skip outlier detection
- …

Automated outlier detection tool

Optimize DPPM levels by:

- Dynamically selecting the most appropriate outlier detection methodology
  - Based on population statistics
  - Library of standard, proprietary and custom algorithms
- Identify outlier devices
  - Look for outliers of sufficient number or magnitude within the test results for a given device
  - User configurable rules-based analysis

Automated outlier detection tool

Test Program Optimization:

- Time To Volume enhancement
  – Reduced engineering effort
- Throughput enhancement
  – Test time reduction
- Quality improvement
  – Tests with significant outliers should be retained
- Repeatable, automated, and objective analysis

Conclusion

- The identification of outliers in parametric test results offers benefits for both product quality and test program optimization
- In practice outlier detection is not straightforward and can be problematic depending upon the population distribution
- The optimal outlier detection algorithm should be identified dynamically for each data set
- An automated system to facilitate outlier detection and analysis is available

References

1. S. S. Sabade, D. M. Walker “Evaluation of Effectiveness of Median of Absolute Deviations Outlier Rejection-based I_{ddQ} Testing for Burn-in Reduction”, IEEE VLSI Test Symposium, April 2002
2. T. Henry and T. Soo “Burn-in Elimination of a High Volume Microprocessor using I_{ddQ}” Intl Test Conference, Washington D.C. October 1996 pp. 242-249.
3. T. Barrette et al., “Evaluation of Early Life Failure Screening Methods”, IEEE International Workshop on I_{ddQ} Testing 1996, Washington D.C. October 1996 pp. 14 –17