Binning of Devices with X-IDDQ

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Outline

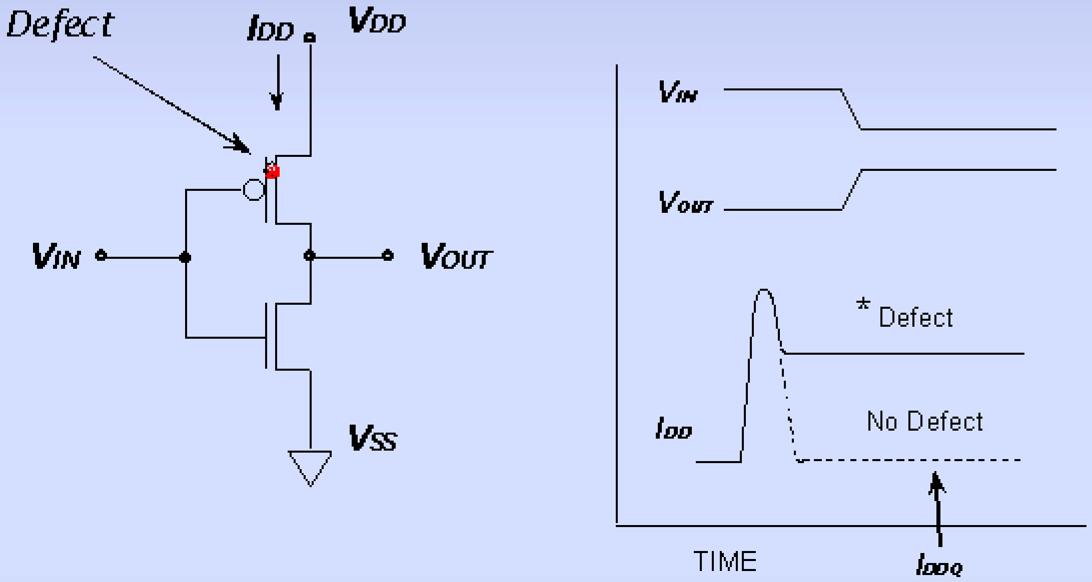
1. Introduction
   - IDDQ testing
   - Previous work (PCA & X-IDDQ)
2. Binning of devices
   - Evaluation of Binning
   - The divide-by-three technique
   - Extended binning
3. Sensitivity of Binning
4. Online Binning
5. Conclusion

Introduction

- With continuous increase of integration densities on a chip, the problem of IC testing has become a complex task.
- Testing of a complex ASIC costs approximately 30% of the overall manufacturing costs.
- IC manufacturers use several test methodology – operational, defect based tests to ensure that manufactured chip fully functional.
- Since this involves significant testing time and cost, test optimizations becomes an important requisite.
- Applying all tests to all the devices would be an inefficient strategy.

IDDQ testing

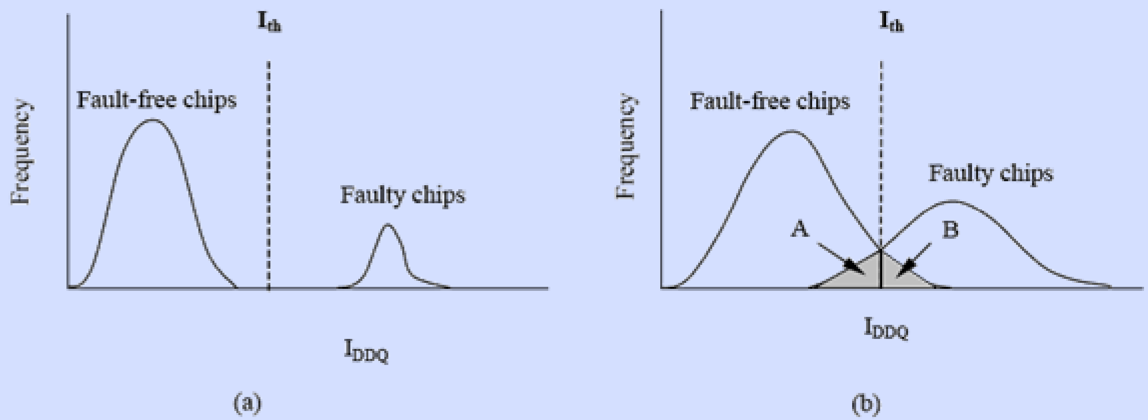
- Proven to be a very effective test optimization technique.
- IDDQ testing Involves the measurement of the steady state current drawn from the power supply after application of a test vector.



IDDQ testing for CMOS circuits

IDDQ testing……

- ➢ High IDDQ could indicate the presence of a fault.
- ➢ However as fault-free and faulty IDDQ distributions overlap, it becomes difficult to discriminate faulty chips.
- ➢ Single threshold could lead to rejection of good devices (B) or test escapes (A).
- ➢ Therefore background leakage currents could cause a concern in threshold IDDQ.



Disadvantages of single threshold

IDDQ testing……

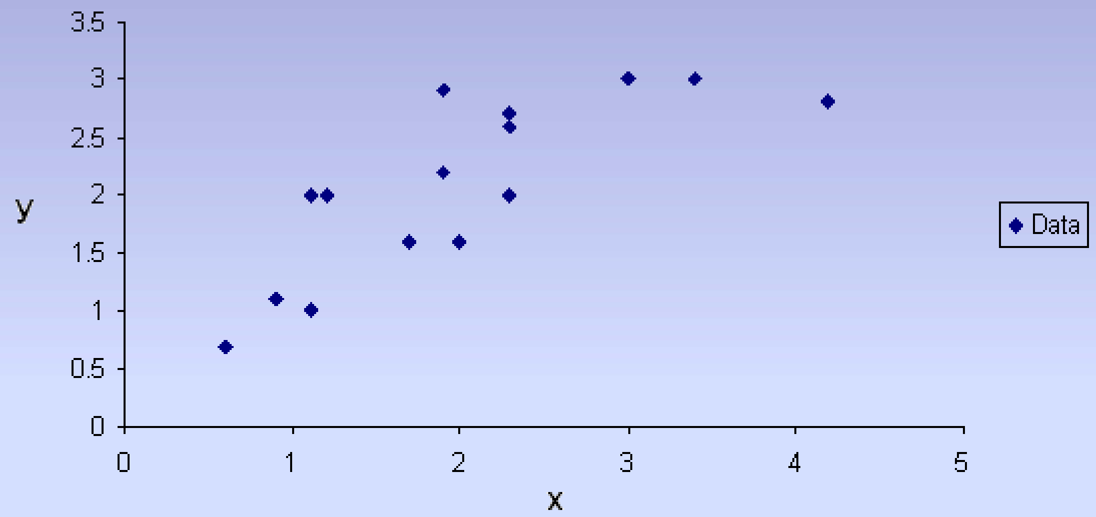
- Statistical techniques for defect detection with IDDQ data has been proposed to retain the effectiveness of IDDQ testing in deep submicron technologies.
- These techniques aim at variance reduction to distinguish faulty and fault free devices -
  - Delta IDDQ
  - Clustering based techniques
  - Independent Component Analysis
- Use more than one IDDQ vector to determine the pass/fail criteria

Principal Component Analysis

- Technique used to identify patterns in data.
- Advantageous in representing multi-dimensional dataset where graphical representation could be cumbersome.
- PCA reduces the dimensionality of the dataset whilst retaining the amount of information present in the same.
- Achieved by transforming the set of data of a higher dimensions (p) to a new set of variables of a lower dimension (q) called “Principal Components”.
- Components with low variance - **“Least Significant Principal Components”** and the components with the high variance - **“Most Significant Principal Components”**.

Example of PCA

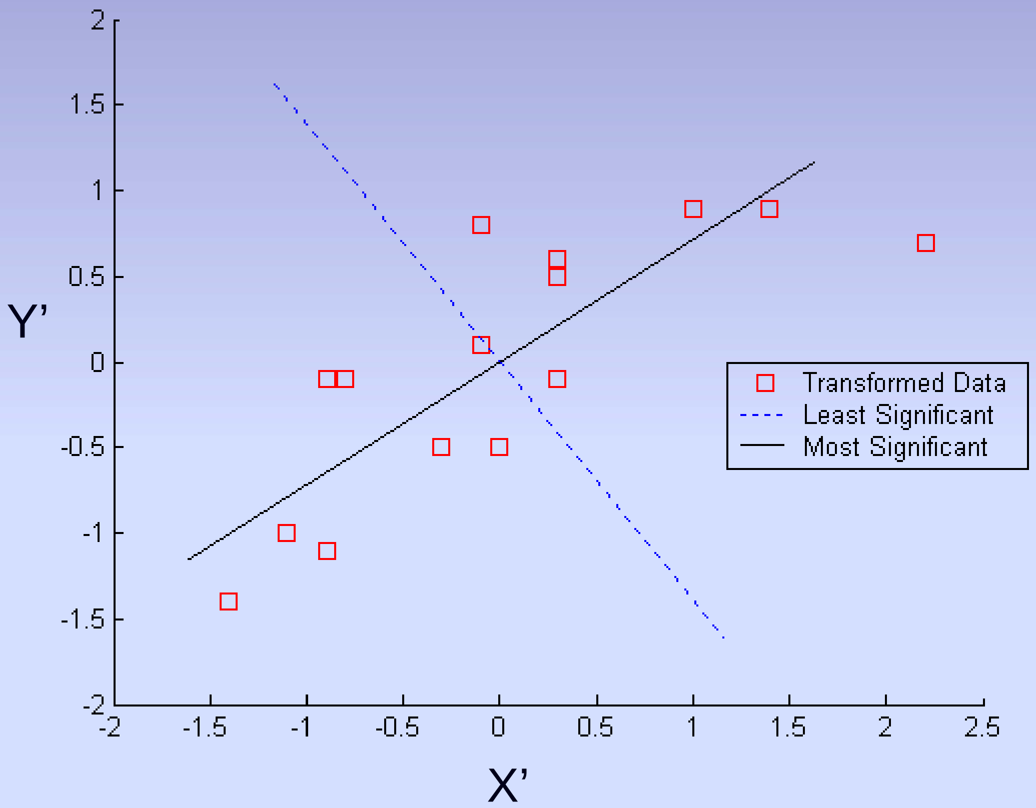
X	Y
2.3	2.6
0.6	0.7
1.9	2.9
1.9	2.2
3.4	3.0
4.2	2.8
2.3	2.7
2.0	1.6
1.1	1.0
1.7	1.6
0.9	1.1
1.2	2.0
3.0	3.0
2.3	2.0
1.1	2.0



Original Data Set

Example of PCA.....

X'	Y'
0.3	0.5
-1.4	-1.4
-0.1	0.8
-0.1	0.1
1.4	0.9
2.2	0.7
0.3	0.6
0.0	-0.5
-0.9	-1.1
-0.3	-0.5
-1.1	-1.0
-0.8	-0.1
1.0	0.9
0.3	-0.1
-0.9	-0.1

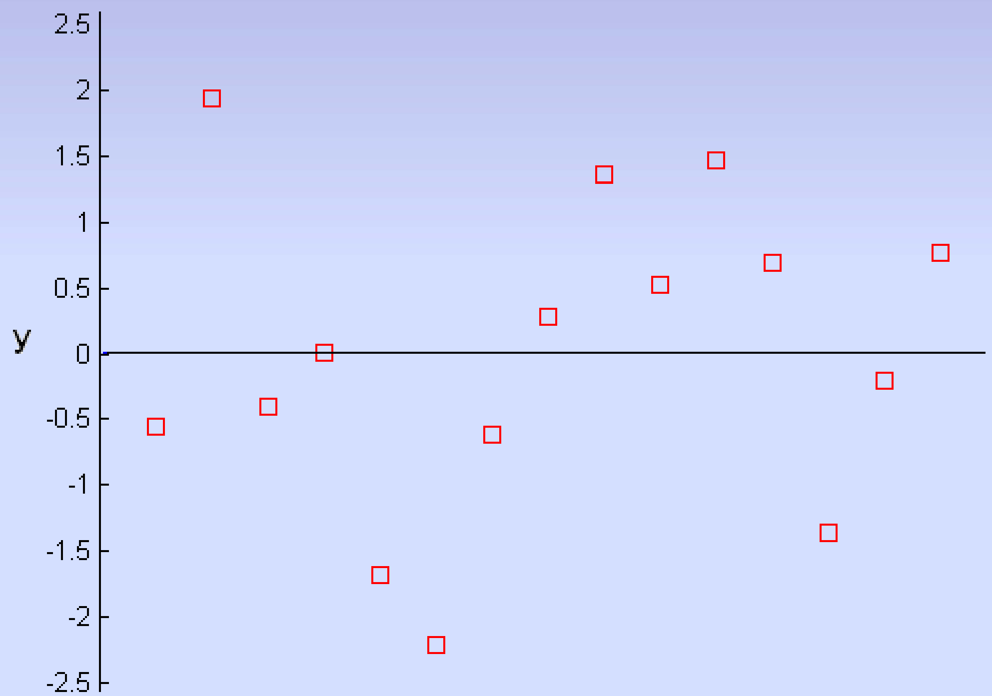


$$\text{Eigen Vectors} = \begin{pmatrix} 0.584 & -0.812 \\ -0.812 & -0.584 \end{pmatrix} \qquad \text{Eigen Values} = \begin{pmatrix} 0.15 & 0 \\ 0 & 1.398 \end{pmatrix}$$

Example of PCA.....

New Data
-0.5527
1.937
-0.4032
0.0057
-1.6791
-2.2116
-0.6111
0.275
1.3559
0.5185
1.4599
0.6907
-1.3545
-0.2022
0.7718

New Data with Reduced Dimension



PCA on IDDQ testing

Let **M** be (nxp) matrix of IDDQ measurements where n is the number of devices and p is number of test vectors per device

Using Singular Value Decomposition,

$$\mathbf{M} = \mathbf{USV^T}$$

$\mathbf{U_{nxp}}$ - gives scaled version of PC scores

$\mathbf{S_{pxp}}$ - diagonal matrix whose squared diagonal values are eigen values arranged in ascending order.

$\mathbf{V^T_{pxp}}$ - rows contains eigen vectors (PCs). **V** is the transformation matrix.

$\mathbf{Z = MV}$ gives the z-score value of devices.

Z-score value of a device is a **"linear combination"** of all the corresponding IDDQ values for a device.

$$Z = \begin{bmatrix} M11 & M12 & M13 & M14 \\ M21 & M22 & M23 & M24 \\ M31 & M32 & M33 & M34 \\ M41 & M42 & M43 & M44 \\ M51 & M52 & M53 & M54 \\ M61 & M63 & M63 & M64 \end{bmatrix} * \begin{bmatrix} V11 & V12 & V13 & V14 \\ V21 & V22 & V23 & V24 \\ V31 & V32 & V33 & V34 \\ V41 & V42 & V43 & V44 \end{bmatrix}$$

nxp pxq

Procedure for X-IDDQ

- Select a set of known good devices called as the training set.
- Perform singular value decomposition => transformation matrix (V).
- On the test data which requires binning, find the Z scores

$$Z=M.V$$

- Obtain the X-statistic using the least or most significant principal components.

X-IDDQ

- To compute X-IDDQ with **"Least Significant Components"**

$$Xi = \log_{10}\left[\max_{p-q+1\le k\le p}\left|\frac{z_{ik}}{\sqrt{l_k}}\right|\right]$$

p - Number of test vectors / device

q - Number of least significant principal components

L_k - k'th variance (Contained in the S matrix)

- To compute X-IDDQ with **"Most Significant Components"**

$$Xi = \log_{10}\left[\max_{1\le k\le q}\left|\frac{z_{ik}}{\sqrt{l_k}}\right|\right]$$

q - Number of most significant principal components

Most significant principal components good for representing data

Least significant principal components good for detecting outliers **

**** IT Jolliffe, "Principal component Analysis", 2nd edition, Springer series, New York, 2002.**

Application to SEMATECH Data

- SEMATECH Data
  - Experiment carried out at IBM Corporation by SEMATECH member companies to investigate the relative effectiveness of tests.
  - 18,466 devices underwent four tests: Stuck-at, Functional, Delay and IDDQ Test. 195 IDDQ test vectors with the category was provided.
  - The device functions as a Bus Interface Controller.
- Classification of Devices based on SEMATECH results :

Category	Description / Sort-Code Key included
All Fail (AF)	Devices that fail all tests. [AF, IO, RR, SR]
All Pass (AP)	Devices that pass all tests. [AP]
Delay Fail (DF)	Devices that only fail Delay test. [1P,2F, 3F]
Functional Fail (FF)	Devices that fail Functional Tests [1F,2A,2D,3I,3T]
Stuck-at Fail (SF)	Devices that fail Stuck-at Tests [1T, 2B, 2C, 2E, 3P]
IDDQ-only Fail (IF)	Devices that only fail single threshold (5uA) IDDQ Test [1I]

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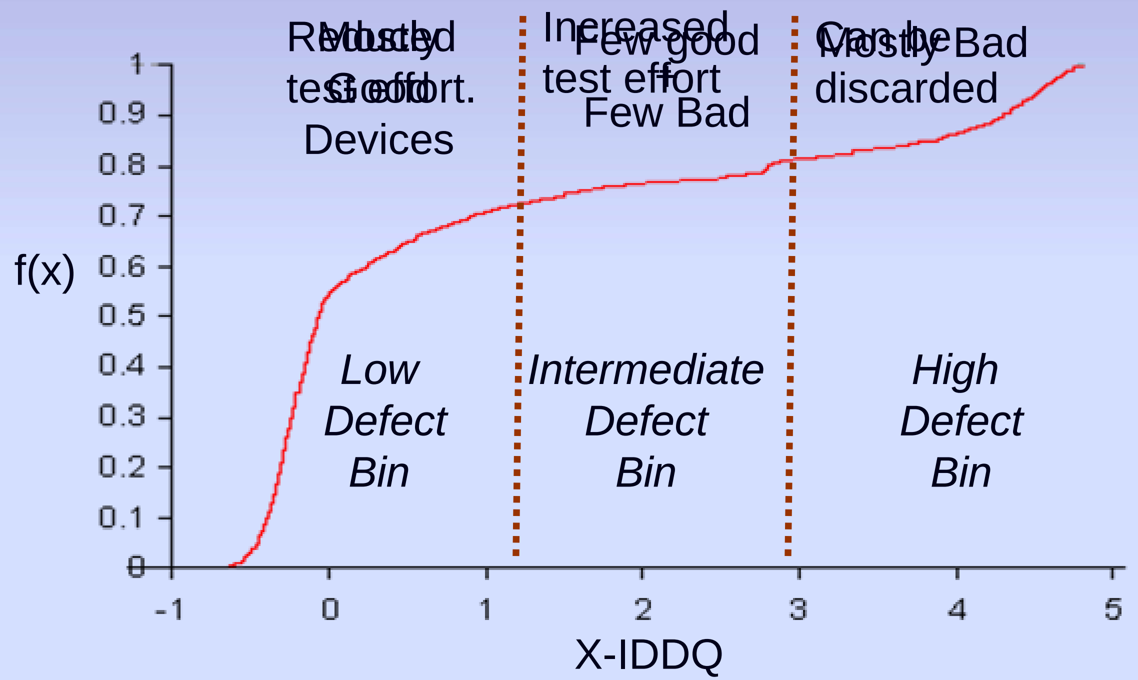
Binning of Devices

- Binning is the process of separation of devices based on quality attributes.
- In an ideal binning scheme, each bin would contain devices of similar characteristics.
- Using the binning technique, the tester can select potential devices for more extensive testing while rejecting some as faulty devices thus reducing test effort, time and resources.

Divide by three binning

The “Divide-by-three” binning technique proposed in the previous work* suggested dividing the entire range of X into three regions



* A Sharma, AP Jayasumana, YK Malaiya, “X-IDDQ: A Novel Defect Detection Technique using IDDQ Data”, VLSI test symposium 2006, Proceedings. 24th IEEE 30 April-4 May 2006 Page(s):6 pp.

Evaluation of Binning

ALL PASS – Devices in SEMATECH lots with category - $$

IDDQ Only fail – Devices in SEMATECH lots with category - 1I

Good Devices – Devices with either '$$' or '1I' category

$$m_{LD}(1) = \frac{\text{All Pass devices in LD BIN}}{\text{Total All Pass devices in Lot}}$$

Indicates fraction of "ALL PASS" devices Captured

$$m_{LD}(2) = \frac{\text{Good devices in LD BIN}}{\text{Total All Pass devices in Lot}}$$

Indicates fraction of "Good Devices" Captured

$$m_{HD}(3) = \frac{\text{All Pass devices in HD BIN}}{\text{Total All Pass devices in Lot}}$$

Indicates fraction of "ALL PASS" devices Lost

$$m_{LD}(4) = \frac{\text{Good devices in LD BIN}}{\text{Total devices in LD BIN}}$$

Indicates "Test Effort" for LD bin.

$$m_{ID}(5) = \frac{\text{Good devices in ID BIN}}{\text{Total devices in ID BIN}}$$

Indicates "Test Effort" for ID bin.

$$m_{HD}(6) = \frac{\text{Bad devices in HD BIN}}{\text{Total bad devices in Lot}}$$

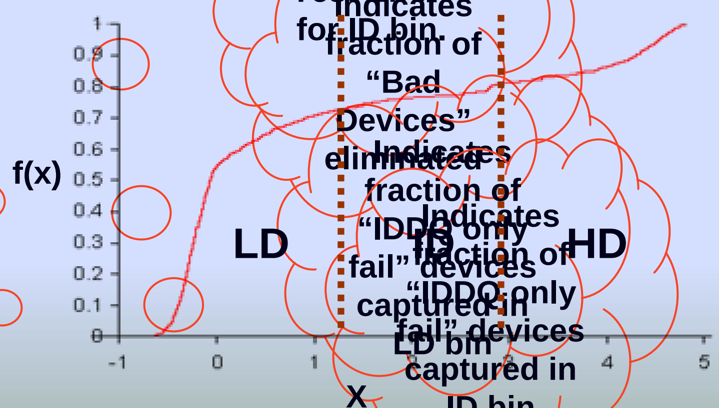
Indicates fraction of "Bad Devices" eliminated

$$m_{LD}(7) = \frac{\text{1I devices in LD BIN}}{\text{Total 1I devices in LOT}}$$

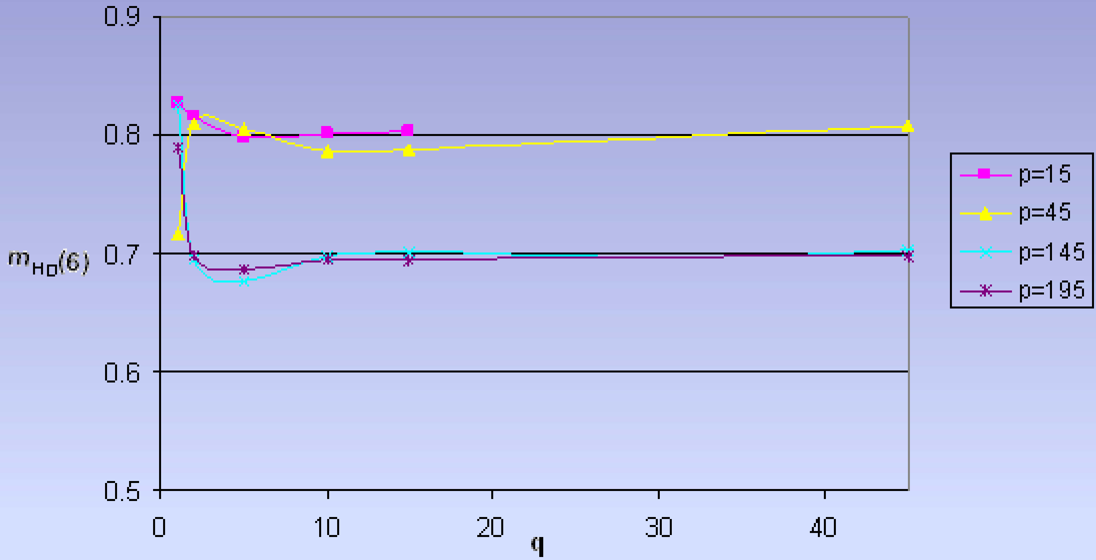
Indicates fraction of "IDDQ only fail" devices captured in LD bin

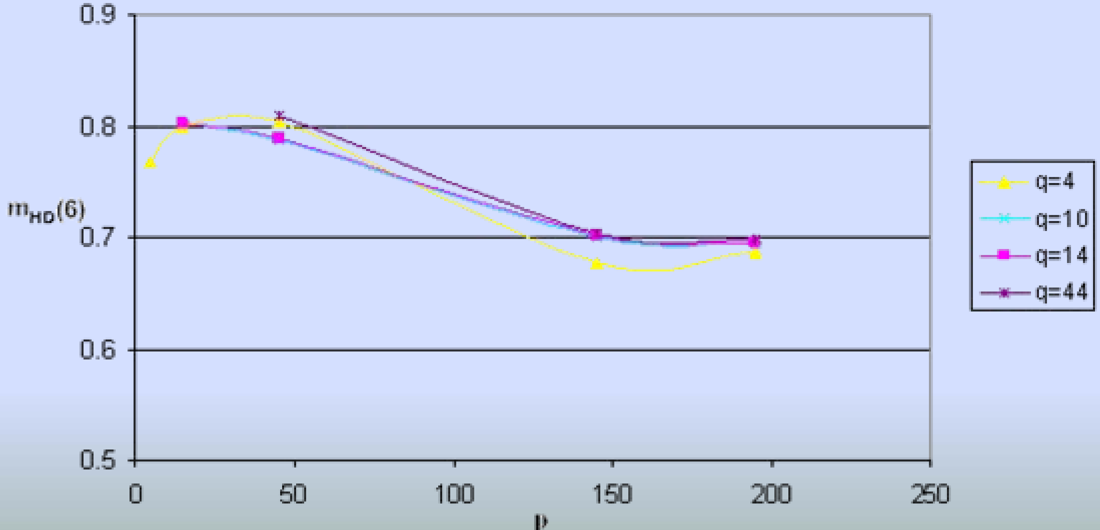
$$m_{ID}(8) = \frac{\text{1I devices in ID BIN}}{\text{Total 1I devices in LOT}}$$

Indicates fraction of "IDDQ only fail" devices captured in ID bin



Evaluation of divide-by-three binning

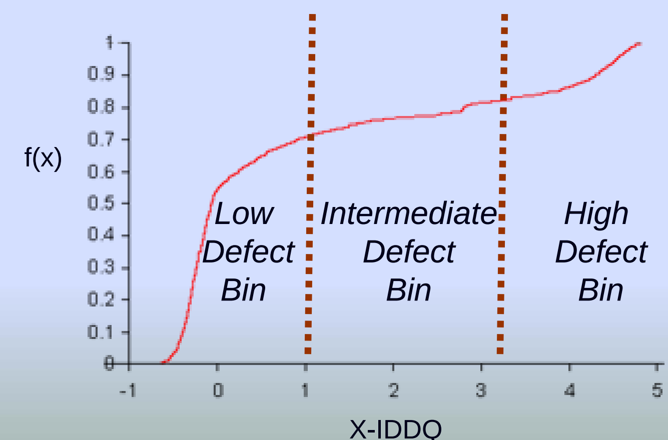




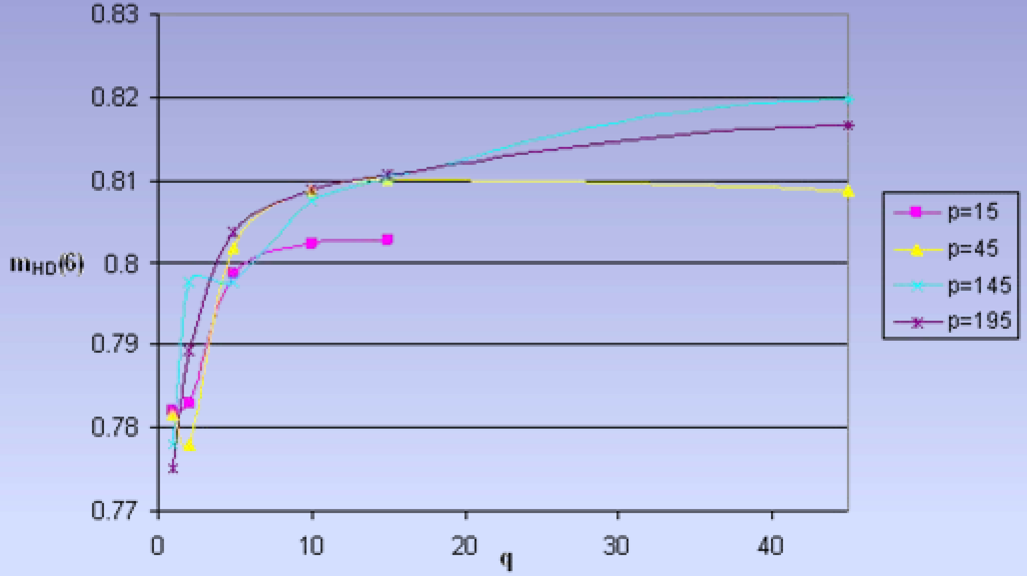
$$m_{HD}(6) = \frac{\text{Bad devices in HD BIN}}{\text{Total bad devices in Lot}}$$

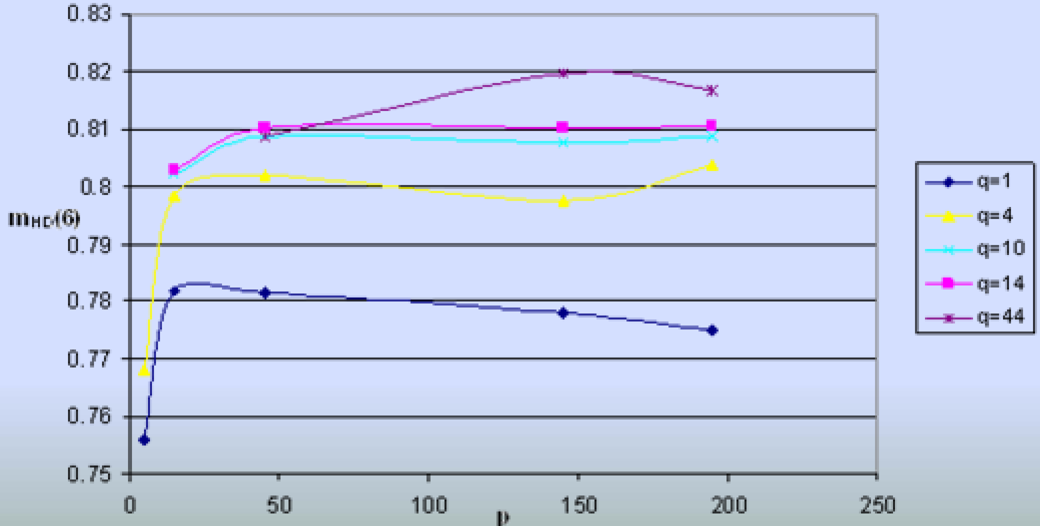
Variation of the measure $m_{HD}(6)$ with p and q.

The X-statistic was computed with the **"least significant principal components"**.



Evaluation of divide-by-three binning

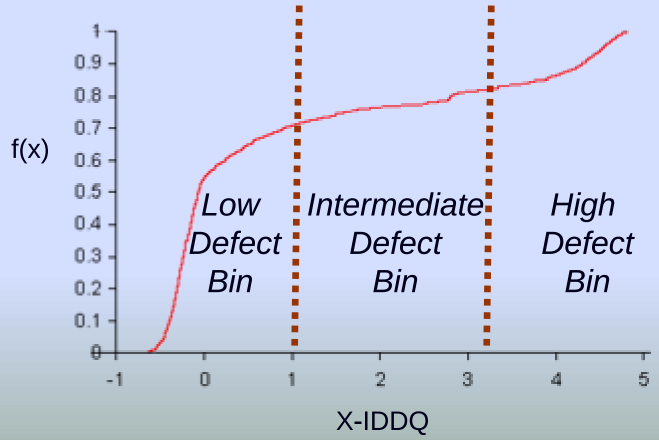




$$m_{HD}(6) = \frac{\text{Bad devices in HD BIN}}{\text{Total bad devices in Lot}}$$

Variation of the measure $m_{HD}(6)$ with p and q.

The X-statistic was computed with the **"most significant principal components"**.



Evaluation of divide-by-three binning

- By selecting fewer least significant principal components (q) would cause -
  - $m_{HD}(6)$ high=> Increase bad devices eliminated
  - $m_{LD}(4)$ high => Reduced test effort
  - $m_{LD}(7)$ low => Reduced burn-in test on LD bin
  - $m_{ID}(8)$ high => Increased burn-in on ID bin
- The same effect is seen when we select larger subset of the most significant principal components

$$m_{HD}(6) = \frac{\text{Bad devices in HD BIN}}{\text{Total bad devices in Lot}}$$

$$m_{LD}(4) = \frac{\text{Good devices in LD BIN}}{\text{Total devices in LD BIN}}$$

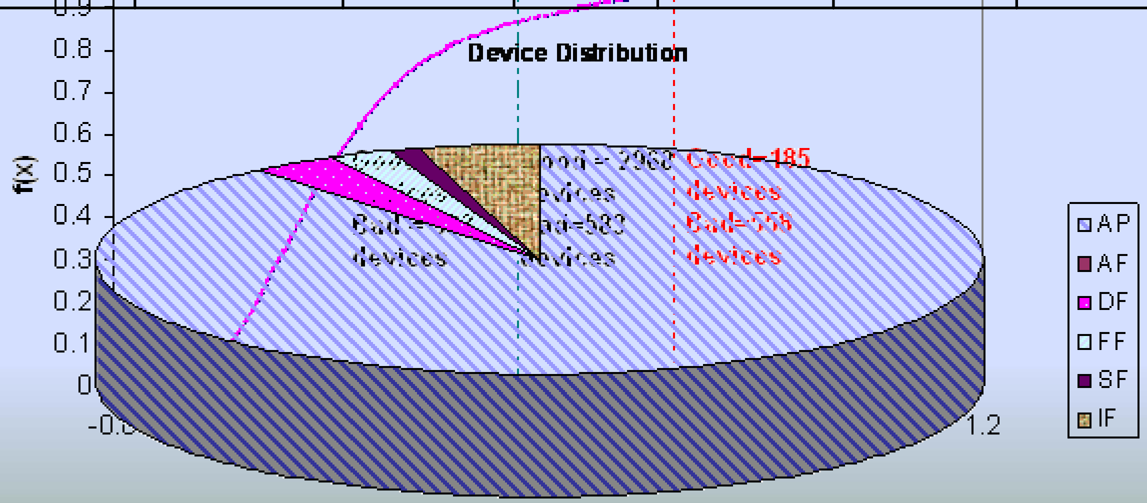
$$m_{LD}(7) = \frac{\text{1I devices in LD BIN}}{\text{Total 1I devices in LOT}}$$

$$m_{ID}(8) = \frac{\text{1I devices in ID BIN}}{\text{Total 1I devices in LOT}}$$

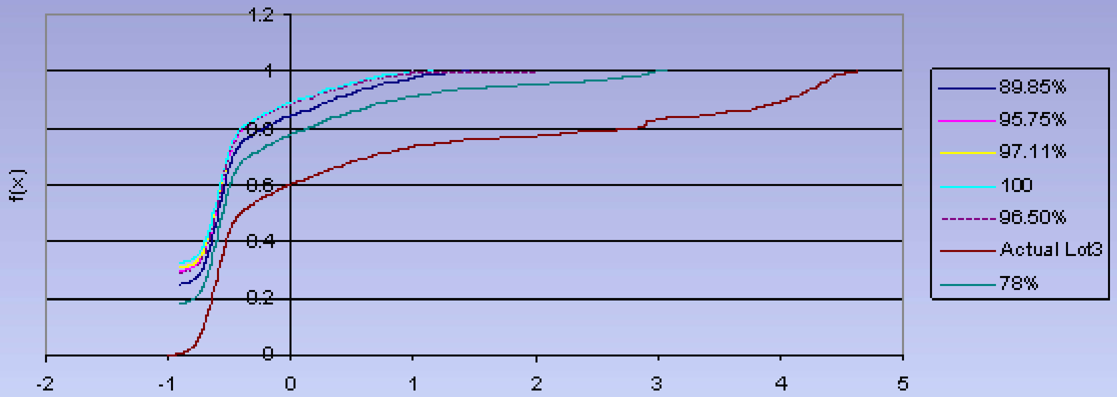
Limitations of divide-by-three binning

- Divide-by-three binning approach worked well for SEMATECH lots.
- Contained very high fraction of bad devices unlike practical lots.
- Applied divide-by-three binning on lots which closely resemble practical IC manufacturing Lots.

Category	AP	AF	DF	FF	SF	IF
devices	11263(89.2%)	10(0.07%)	384(3%)	252(1.99%)	167(1.32%)	550(4.35%)



Limitations of divide-by-three binning



Artificial lots with different percentage of good devices

$$m_{HD}(3) = \frac{\text{All Pass devices in HD BIN}}{\text{Total All Pass devices in Lot}}$$

% of good devices in the lot	LD BIN LIMIT	ID BIN LIMIT	Good Devices in HD BIN	measure $m_{LD}(1)$	measure $m_{HD}(3)$	measure $m_{LD}(4)$	measure $m_{HD}(6)$
78	0.4149949	1.742401	0	1	0	0.9491	0.5541
89.85	-0.1236300	0.665152	3	0.978	0.0016	0.9614	0.3491
95.75	-0.2195182	0.473375	25	0.941	0.014	0.9650	0.1943
96.5	0.08769736	1.087806	0	0.998	0	0.9891	0.2123
97.11	-0.2195182	0.473375	56	0.891	0.0314	0.9986	0.0839
100	-0.2195182	0.473375	85	0.822	0.0477	1	0
original Lot3	0.86124644	2.741659	0	1	0	0.9414	0.616

Various measures for these artificial lots.

Extended Binning

- In this scheme, use the good devices to define the LD bin limit.
- The highest X-IDDQ in the training set is chosen as the LD bin limit.

- Let the binning limits be represented as follows :

  $X_L(d)$ - Lower binning limit with divide-by-three binning technique

  $X_H(d)$ - Higher binning limit with divide-by-three binning technique

  $X_L(e)$ - Lower binning limit with extended binning technique

  $X_H(e)$ - Higher binning limit with extended binning technique

Procedure for Extended Binning

- Select a set of known good devices to form the training set (T).
- In order to compute LD bin limit, Choose M_{good}=training set and compute the X-IDDQ values of the devices in the training set.

$$Z = M_{good} * V; \qquad Xi = \log_{10}\left[\max_{p-q+1 \le k \le p}\left|\frac{z_{ik}}{\sqrt{l_k}}\right|\right]$$

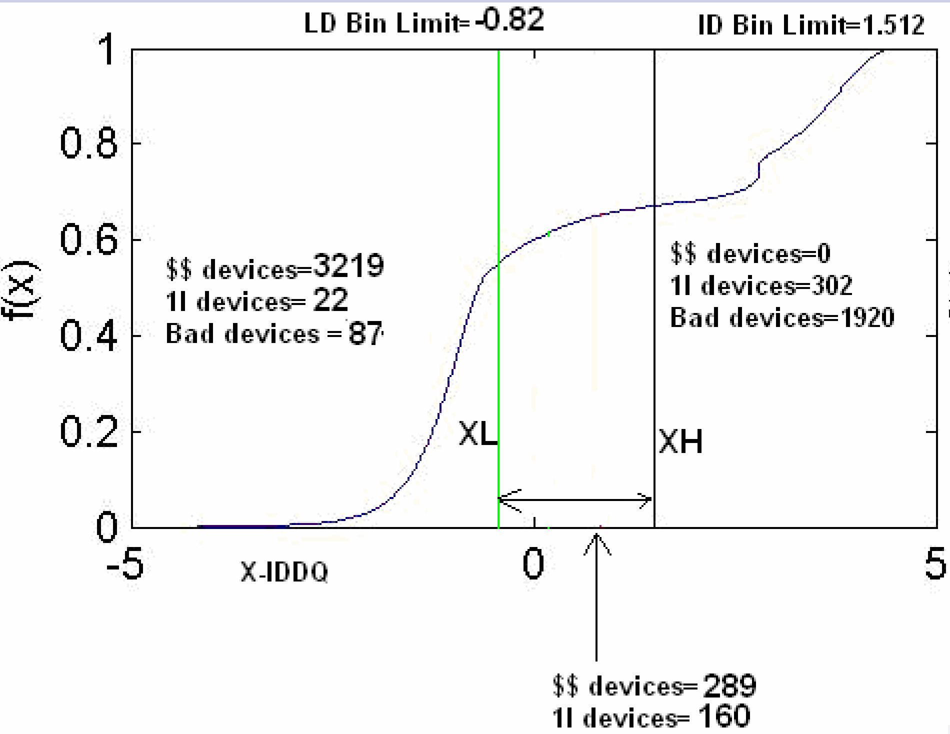
- Choose the highest X-IDDQ of this range as the LD bin limit $X_L(e)$.
- Now compute the X-IDDQ values on the devices in the test lot (M_{test}).

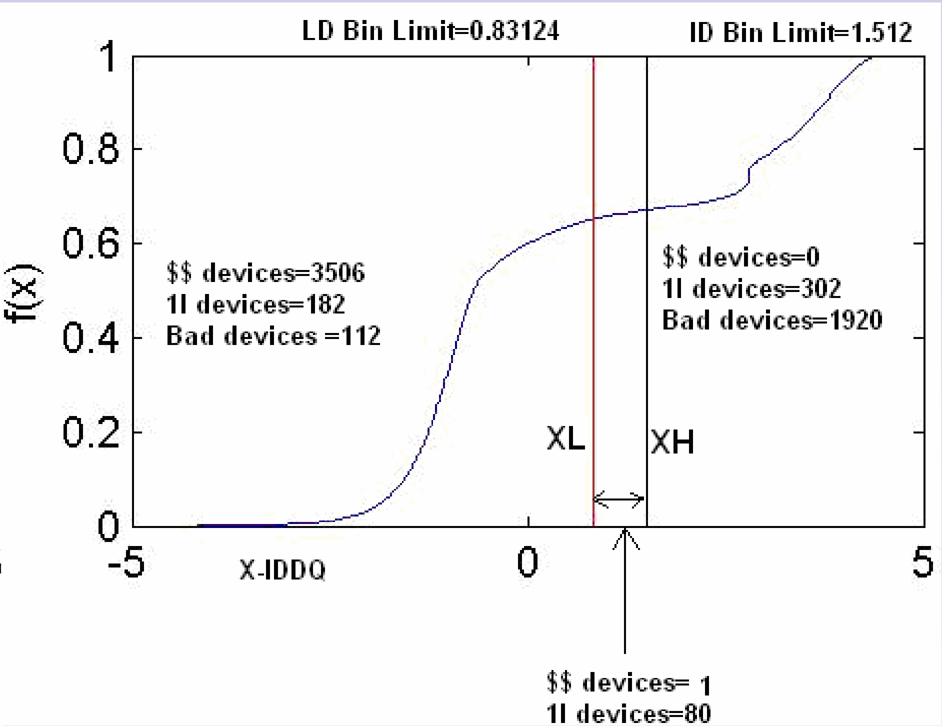
$$Z = M_{test} * V; \qquad Xi = \log_{10}\left[\max_{p-q+1 \le k \le p}\left|\frac{z_{ik}}{\sqrt{l_k}}\right|\right]$$

- Divide the entire range of X values into three regions and use the upper limit $X_H(d)$ to define the bin limit $X_H(e)$.

Extended Binning

LOT1 of SEMATECH data

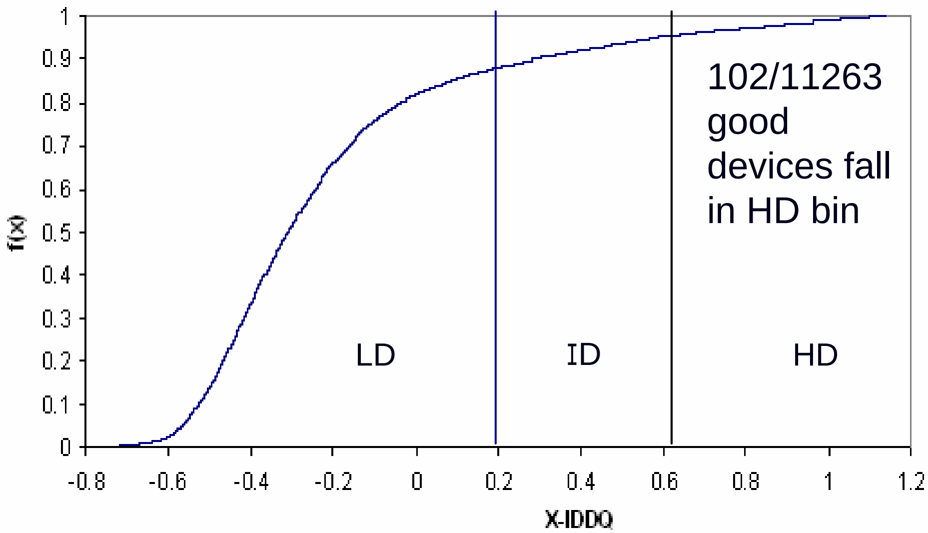


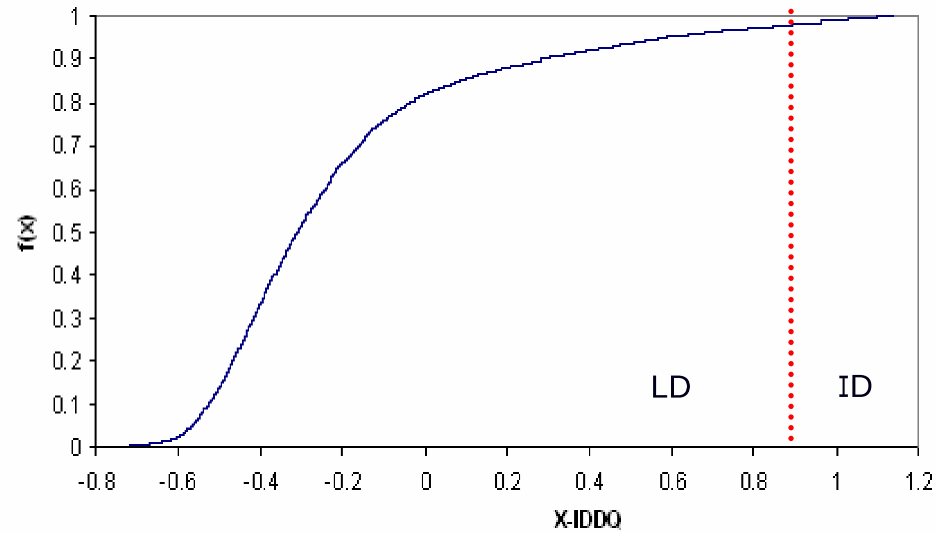


With divide-by-three binning technique

With extended binning technique

Extended Binning





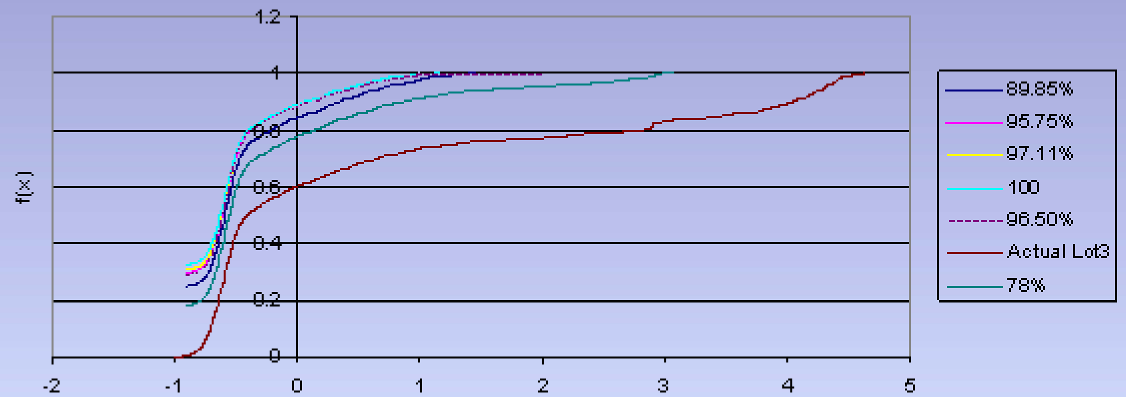
$X_L(d)$=-1.81 $X_H(d)$=-0.12

$X_H(e)$=-0.12 $X_L(e)$=0.81

Artificial lot containing 89.2% “All Pass” devices

$X_L(e) > X_H(e)$

Extended Binning



Artificial Lots

% of good devices	LD BIN LIMIT	ID BIN LIMIT	Good Devices in HD BIN	measures $m_{LD}(1)$	measure $m_{HD}(3)$	measure $m_{LD}(4)$	measure $m_{HD}(6)$
78	1.1839	1.742401	0	0.9983	0	0.9710	0.6712
89.85	1.1839	-	0	1	0	0.9676	0.2871
95.75	1.1839	-	0	1	0	0.9481	0.1582
96.5	1.1839	-	0	1	0	0.9810	0.1791
97.11	1.1839	-	0	1	0	0.9896	0.0107
100	1.1839	-	0	1	0	1	0
original Lot3	1.1839	2.741659	0	0.9934	0	0.9770	0.7897

Various measures computed using the extended-binning technique

Extended Binning……..

- To Summarize ……
  - With extended binning technique, the lower binning limit captures all the “ALL PASS” in the LD bin.
  - More computationally efficient to use the “**Least Significant Principal Components”** to compute X.
  - Extended binning is more applicable to practical lots where the divide-by-three technique could be inefficient.

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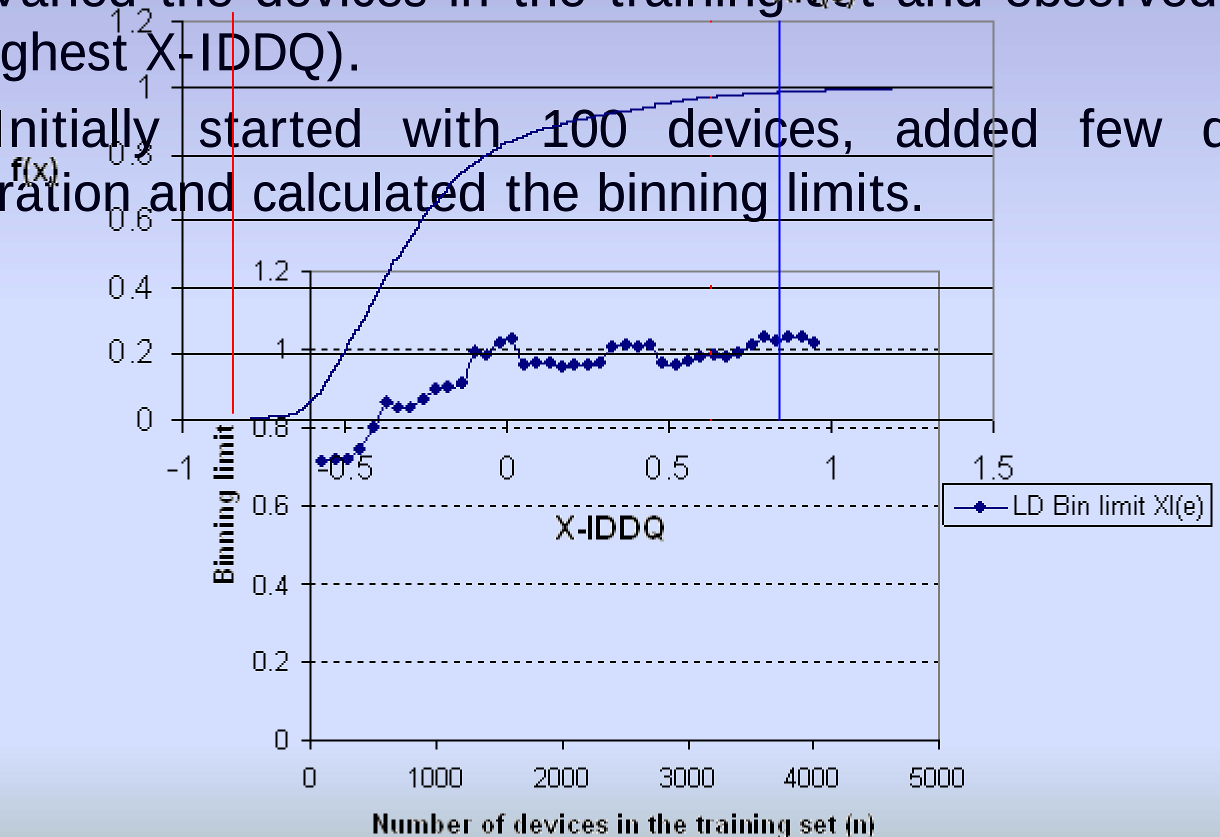
Sensitivity of the binning to training set

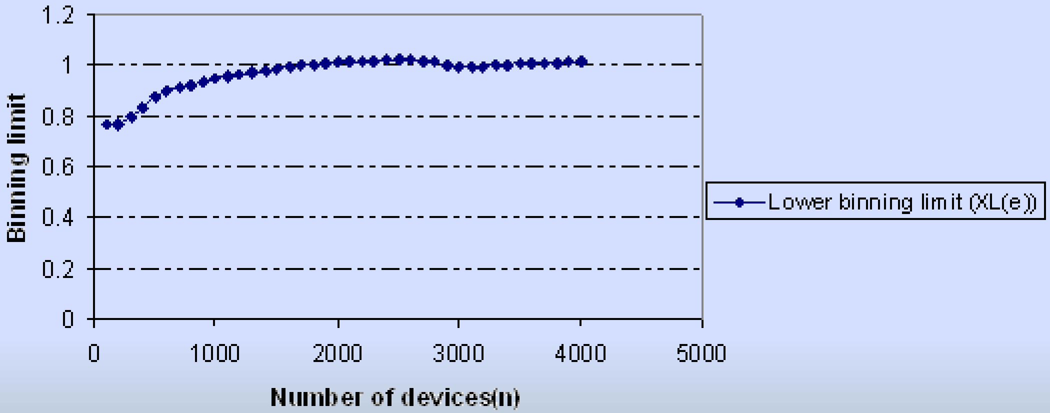
- ➢Lower binning limit $X_L(e)$ for extended binning is determined by highest X-IDDQ value of the devices in the training set.
- ➢Varied the devices in the training set and observed the binning limit (highest X-IDDQ).
- ➢Initially started with 100 devices, added few devices for each iteration and calculated the binning limits.



Lower Binning Limit is sensitive to the training set.

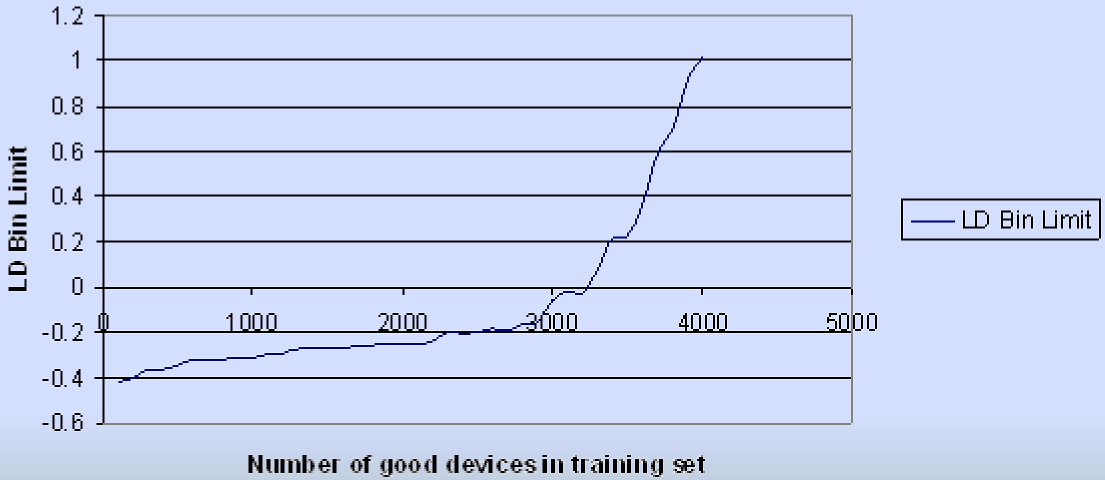
Sensitivity…………

- ➢Sorted the devices in the training set in descending order and calculated the binning limits.
- ➢First 100 devices contained higher average currents than the next 100 devices.
- ➢Low average current devices in the training set do not have much impact on the binning limit.



Sensitivity………..

- Sorted the devices in increasing order and calculated the binning limits.
- First 100 devices contained lower average currents than the next 100 devices.
- Extended binning is sensitive to the devices in the training set.



Sensitivity……….

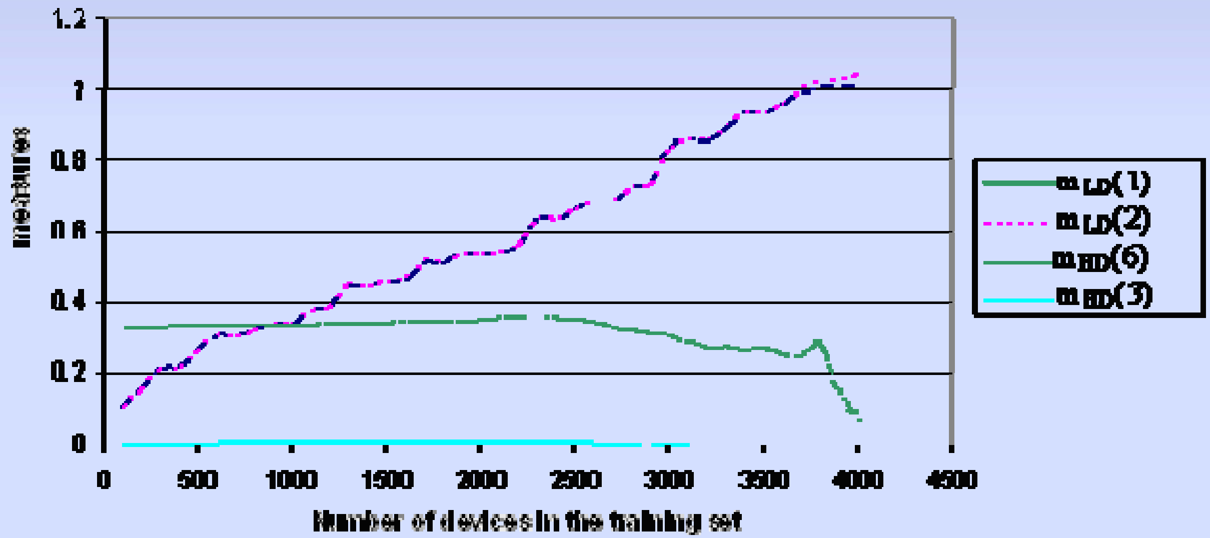
- When training set is updated, not only does binning limit change, but also the X-IDDQ values of the entire lot would change.
- Used Binning limit from previous figure.

$$m_{LD}(1) = \frac{\text{All Pass devices in LD BIN}}{\text{Total All Pass devices in Lot}}$$

$$m_{LD}(2) = \frac{\text{Good devices in LD BIN}}{\text{Total All Pass devices in Lot}}$$

$$m_{HD}(3) = \frac{\text{All Pass devices in HD BIN}}{\text{Total All Pass devices in Lot}}$$

$$m_{HD}(6) = \frac{\text{Bad devices in HD BIN}}{\text{Total bad devices in Lot}}$$



Use a large training set (typically with same size as the test data) and update the training matrix with good devices containing high average currents

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Online Binning

- Fast binning approach for real time sorting of devices.
- As the device arrives from the tester, the X-IDDQ value of the individual device can be calculated.

$$Z_i = \begin{bmatrix} M11 & M12 & M13 & M14 \end{bmatrix} \begin{bmatrix} V11 & V12 & V13 & V14 \\ V21 & V22 & V23 & V24 \\ V31 & V32 & V33 & V34 \\ V41 & V42 & V43 & V44 \end{bmatrix}$$

- Not required to wait for the entire lot to arrive or to re-compute the entire transformation matrix.
- Based on the X-IDDQ value, the device can be assigned to one of the bins to determine the amount of test effort.

Online Binning

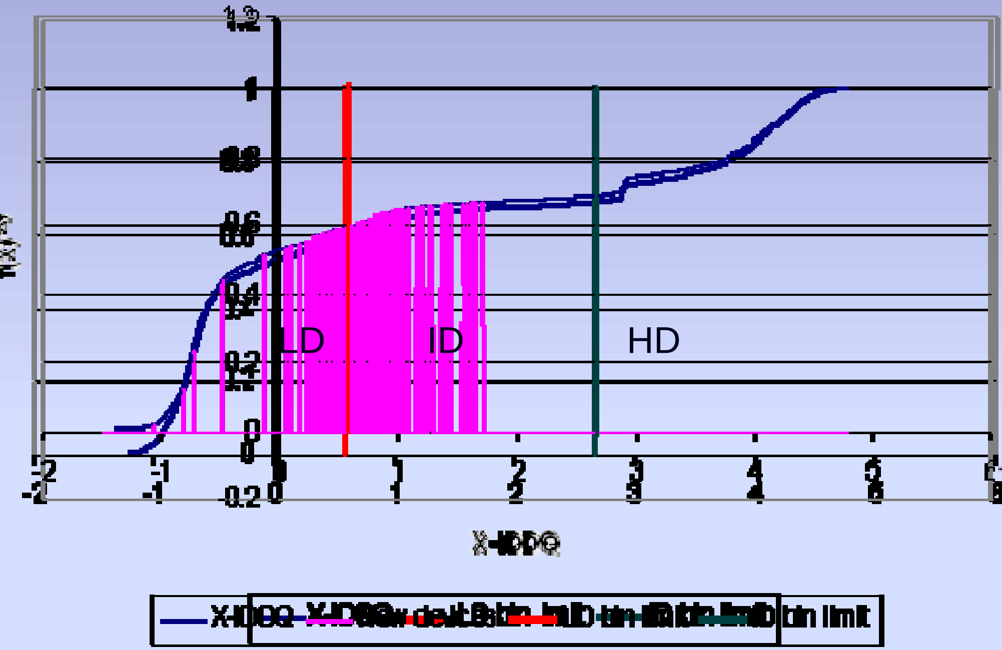
- Two stage procedure -
  1) Identifying the physical bins.
     - Offline binning which forms the bins.
     - Initially a set of pre-screened devices are chosen and the transformation matrix (V) is computed by using SVD.
     - Binning is performed on an initial test lot and the binning limits are calculated to identify the three bins.
  2) Online real-time sorting
     - Actual online binning
     - As each device comes off the production line, the X-IDDQ values are computed without any need to re-compute the entire transformation matrix or to wait for the entire lot to arrive.

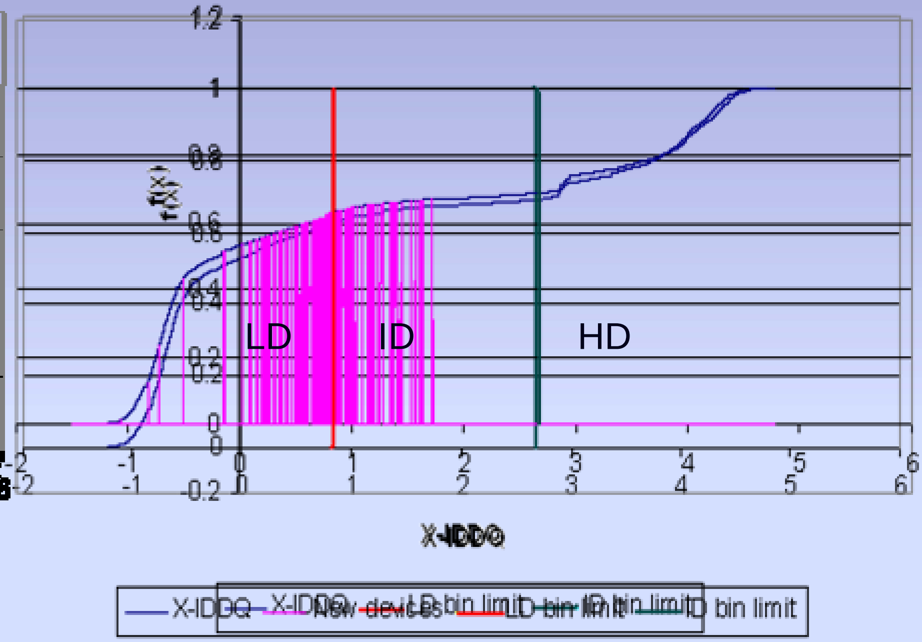
- It would be nice to update the transformation matrix every time a device is identified as good.
- When a device with high X-IDDQ value is tested to be good, include it to the training set and update the transformation matrix.

Demonstration of Online Binning

- Generated a custom lot to demonstrate online binning.
- Identified 4000 good devices for the training set, computed transformation matrix (V) (initial stage)
- Binning was performed on LOT1 as the initial test lot to identify the physical binning limits.

Online Binning……..





Divide by three binning

- 52 good devices in LD bin
- 112 good devices in ID bin

$X_{LD}(d)$=0.583, XHD(d)=2.677

Extended binning

- 95 good devices in LD bin
- 69 good devices in ID bin

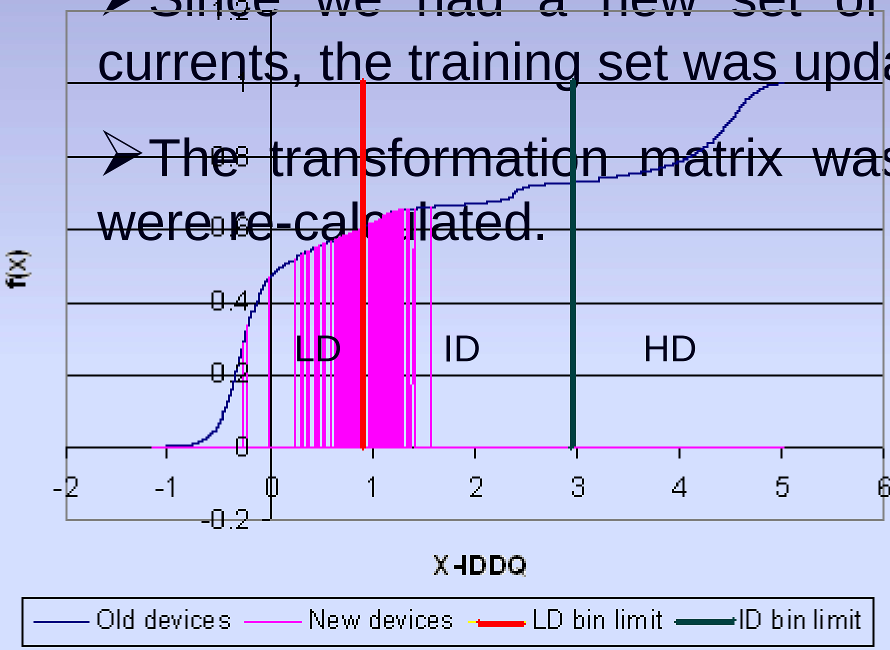
$X_{LD}(e)$=0.834, XHD(e)=2.677

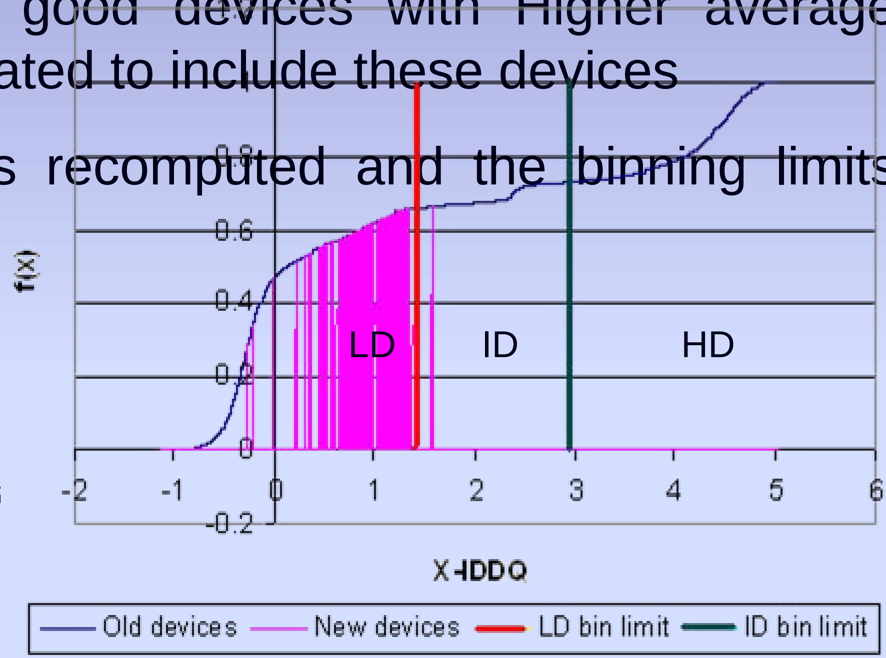
- We added 164 good devices with average currents in between 5-10µA

Online binning……..

Extended Binning More suitable for an online binning implementation.

- ➢Since we had a new set of good devices with Higher average currents, the training set was updated to include these devices
- ➢The transformation matrix was recomputed and the binning limits were re-calculated.





Divide by three binning

67/164 good devices fell in LD bin

97/164 good devices fell in ID bin

Extended binning

160/164 good devices fell in LD bin

4/164 good devices fell in ID bin

Conclusion

- X-IDDQ based statistical techniques help in extracting the fault related information from IDDQ based data.
- We have performed qualitative analysis of the X-IDDQ technique for outlier detection and suggested a binning technique based on the X-IDDQ values of the devices.
- With the help of the cost functions – “measures”, we were able to capture the effectiveness of the binning schemes and also decide on a test strategy.

Conclusion

- About 15-45 test vectors are sufficient to capture most of the good devices and eliminate a large fraction of bad devices.
- When least significant principal components are used the first 5 principal components are sufficient
- When the most significant principal components are used, we need to consider as many as possible.
- Least significant principal components are more efficient.
- The extended-binning technique is sensitive to training set.
- Thus we need to choose training sets of larger sizes, and also containing higher average currents.
- Extended binning suitable for an online implementation.

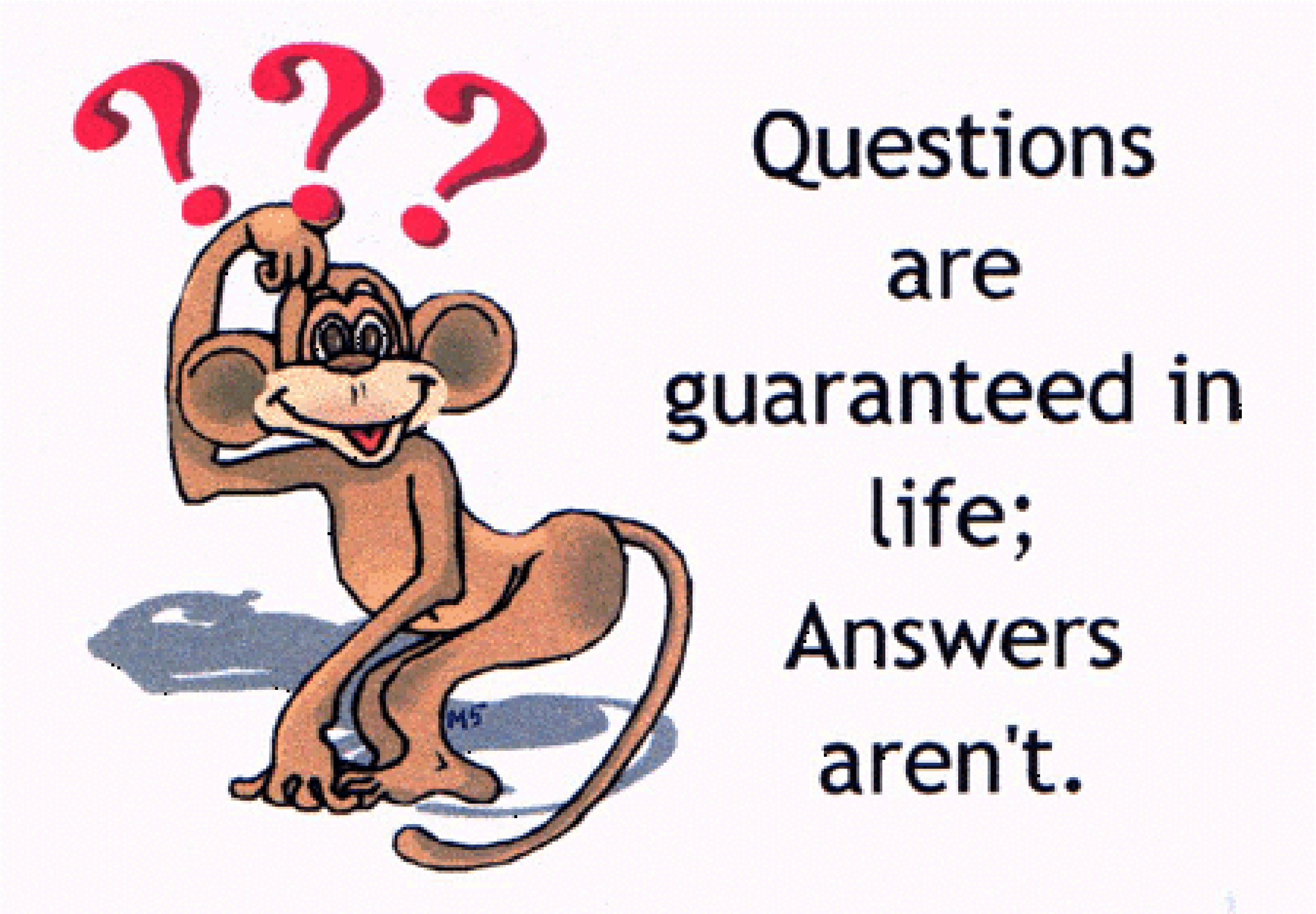
Contribution……

- Evaluating the binning techniques.
- Proposing Alternative Binning strategy
- Burn-in Analysis
- Sensitivity of the Binning
- Implementation of an online binning scheme.

Future work

- Extended binning would require improvement in terms of the upper binning limit $X_H(e)$
- Binning techniques need to incorporate other parameters such as Max Frequency, Min VDD, etc along with the other IDDQ measurements.
- Need to experiment this research on some more IDDQ data from practical IC manufacturing lots.

Questions / Comments or Suggestions ?




Merry Christmas