Prognostic/Diagnostic Health Management (PHM) System for FAB Efficiency

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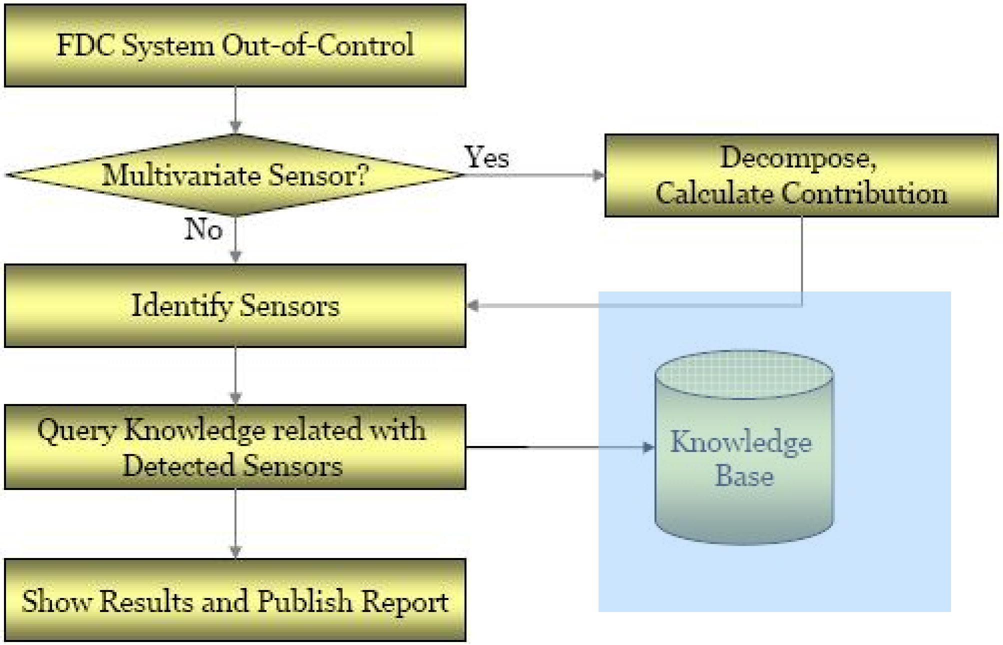
Outline

- Introduction
  - Industry Trend
- PHM – What?
- Method
- Results
- Conclusion

Industry Trend: APC/AEC 2005 Presentation from Samsung

- System Operations Flow Chart



APC/AEC 2005 / Samsung Electronics Co., Ltd. "An Application of Multivariate Statistics in Detecting Equipment Changes" Presenter: Lee, Seungjun

Industry Trend:
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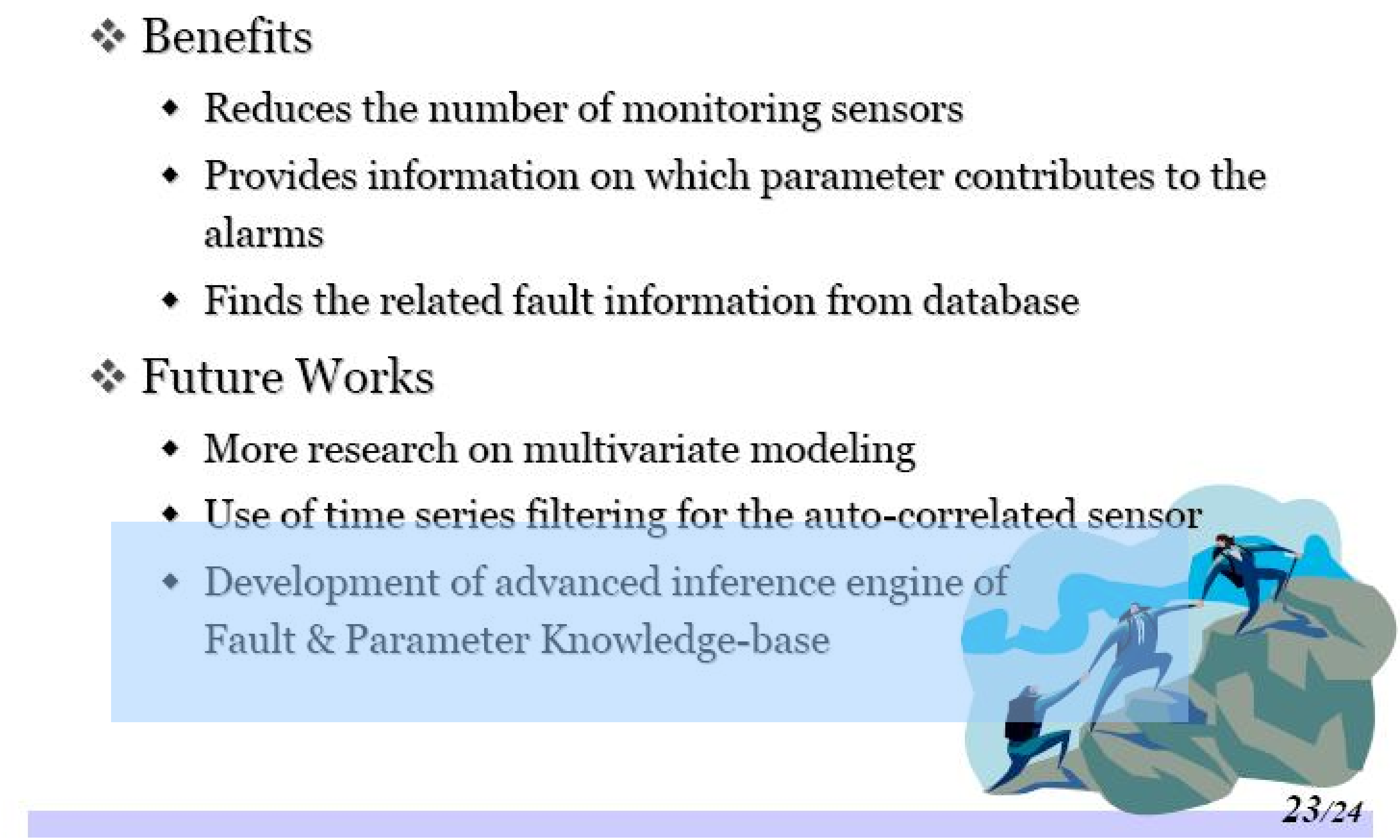
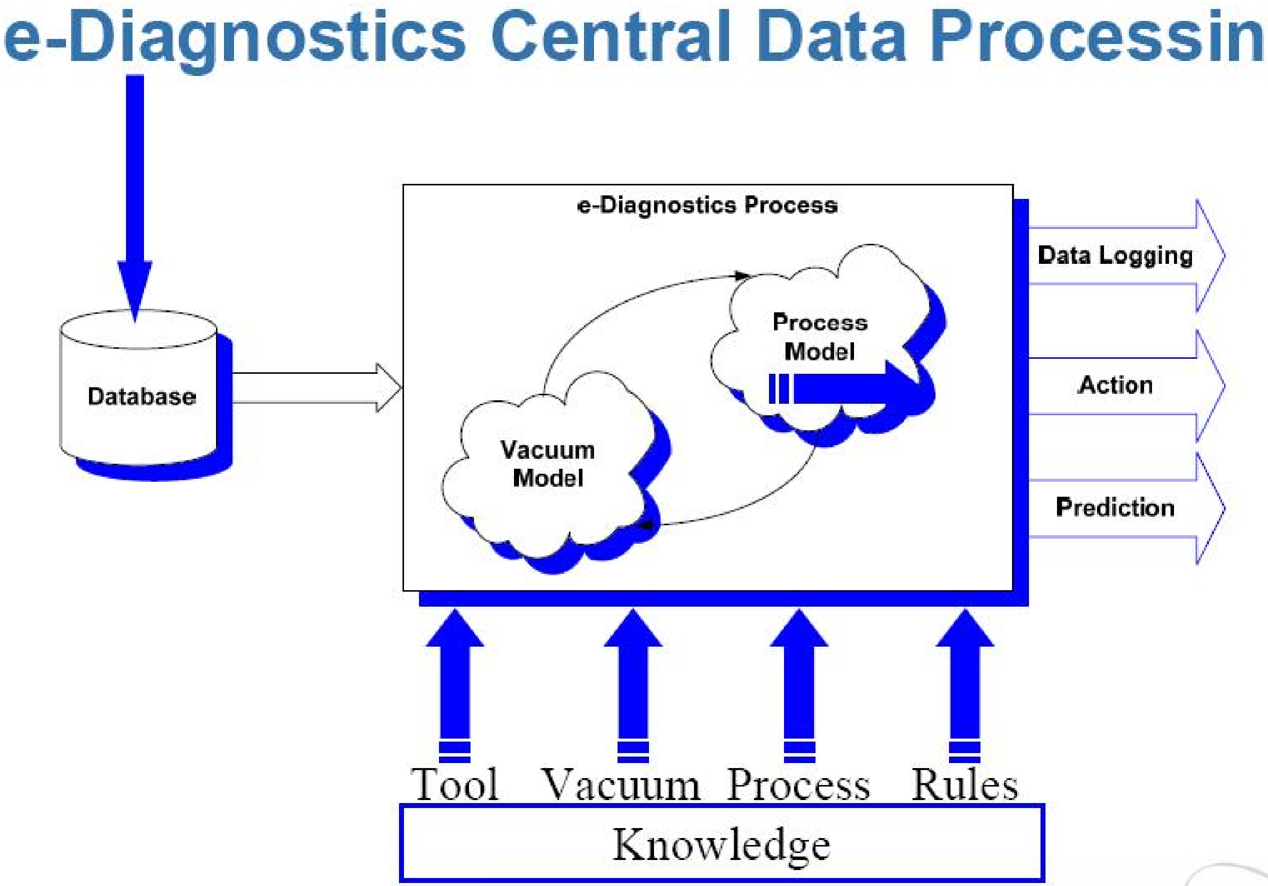


- Benefits
  - Reduces the number of monitoring sensors
  - Provides information on which parameter contributes to the alarms
  - Finds the related fault information from database
- Future Works
  - More research on multivariate modeling
  - Use of time series filtering for the auto-correlated sensor
  - Development of advanced inference engine of Fault & Parameter Knowledge-base

23/24

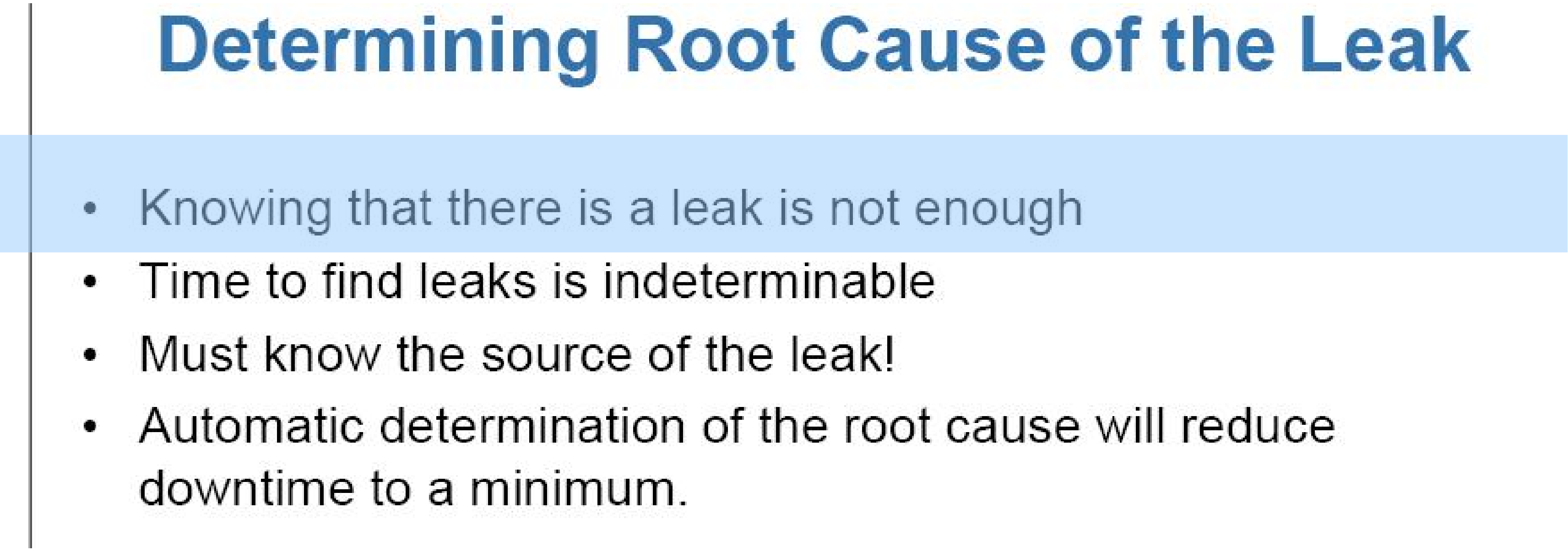
APC/AEC 2005 / Samsung Electronics Co., Ltd. "An Application of Multivariate Statistics in Detecting Equipment Changes" Presenter: Lee, Seungjun

Industry Trend: APC/AEC 2005 Presentation from Helix Tech.



APC/AEC 2005 / **Helix Technology Corporation "Predictive Capability Enabled by a Deterministic Method of Analysis or Real World Vacuum System e-Diagnostics" Presenter: Gaudet, Peter**

Industry Trend:
APC/AEC 2005 Presentation from Helix Tech.

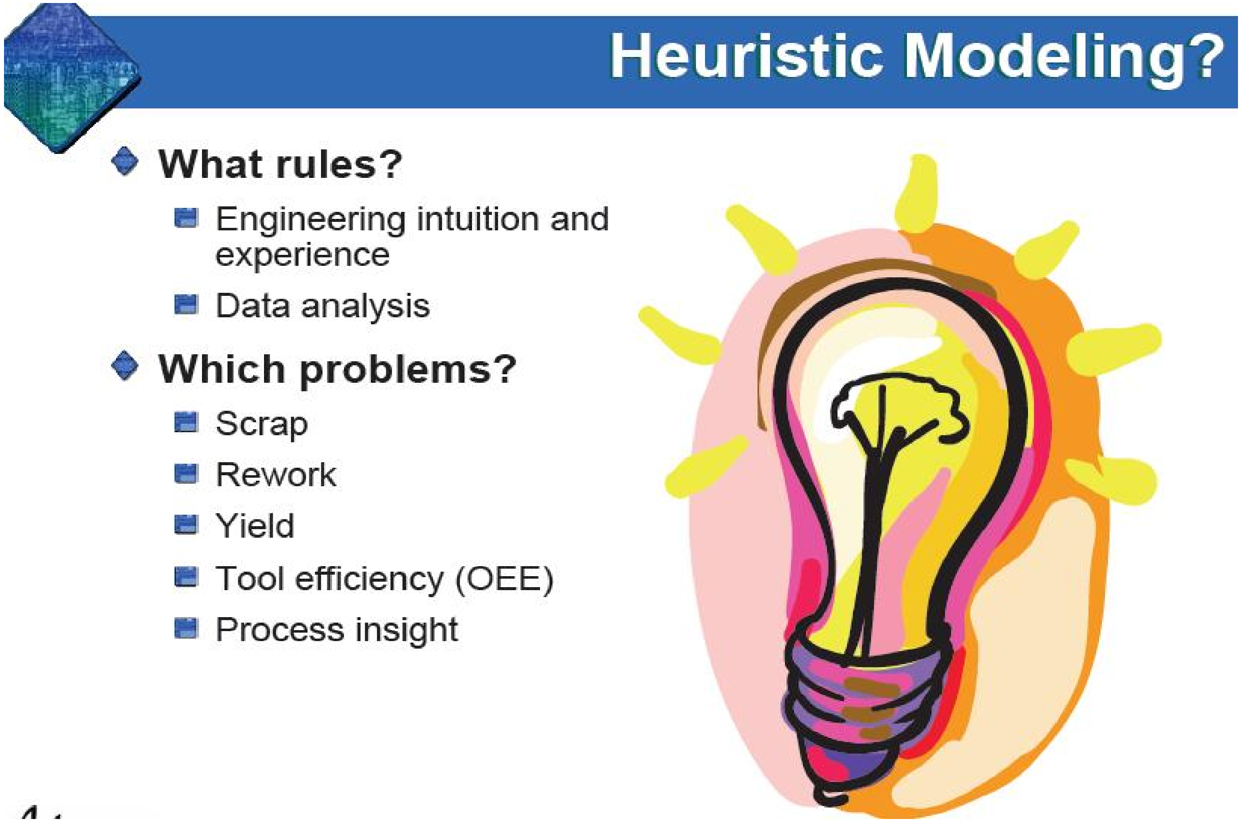


Determining Root Cause of the Leak

- Knowing that there is a leak is not enough
- Time to find leaks is indeterminable
- Must know the source of the leak!
- Automatic determination of the root cause will reduce downtime to a minimum.

APC/AEC 2005 / Helix Technology Corporation "Predictive Capability Enabled by a Deterministic Method of Analysis or Real World Vacuum System e-Diagnostics" Presenter: Gaudet, Peter

Industry Trend:
APC/AEC 2005 Presentation from Adventa

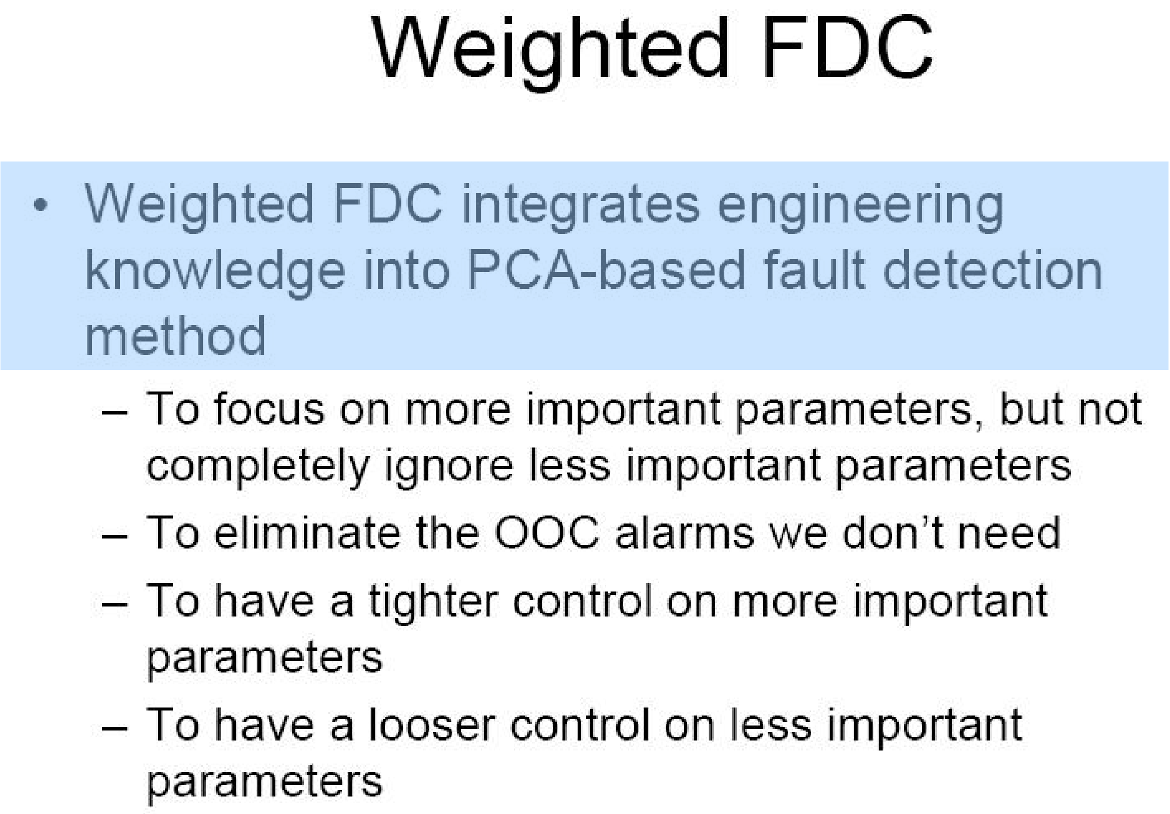


Heuristic Modeling?

- **What rules?**
  - Engineering intuition and experience
  - Data analysis
- **Which problems?**
  - Scrap
  - Rework
  - Yield
  - Tool efficiency (OEE)
  - Process insight

APC/AEC 2005 / "Reaping the Benefits of Heuristic Fault Modeling" Presenter: Jared Warren,
Adventa Control Technologies

Industry Trend: Weighted FDC APC/AEC 2005 Presentation from Intel

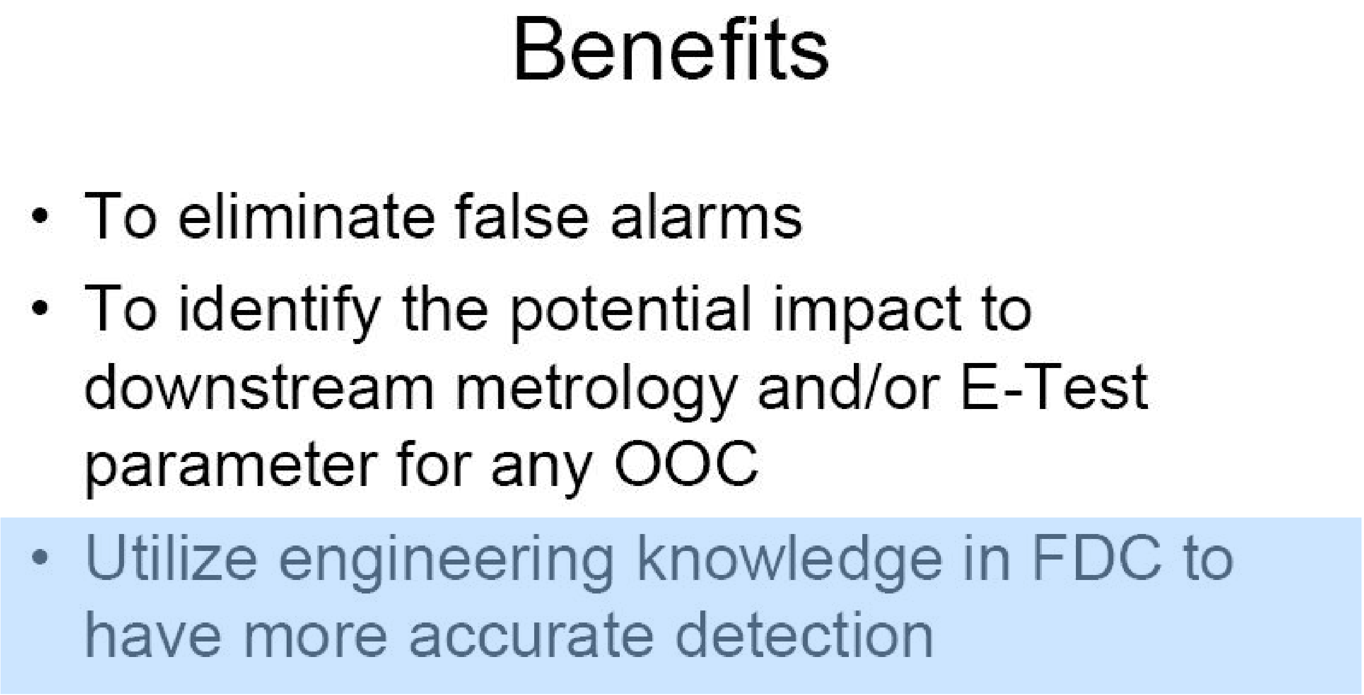


Weighted FDC

- Weighted FDC integrates engineering knowledge into PCA-based fault detection method
  - To focus on more important parameters, but not completely ignore less important parameters
  - To eliminate the OOC alarms we don’t need
  - To have a tighter control on more important parameters
  - To have a looser control on less important parameters

APC/AEC 2005 / Intel Corporation "Weighted Fault Detection and Classification" Presenter: Mao, John

Industry Trend: Weighted FDC APC/AEC 2005 Presentation from Intel

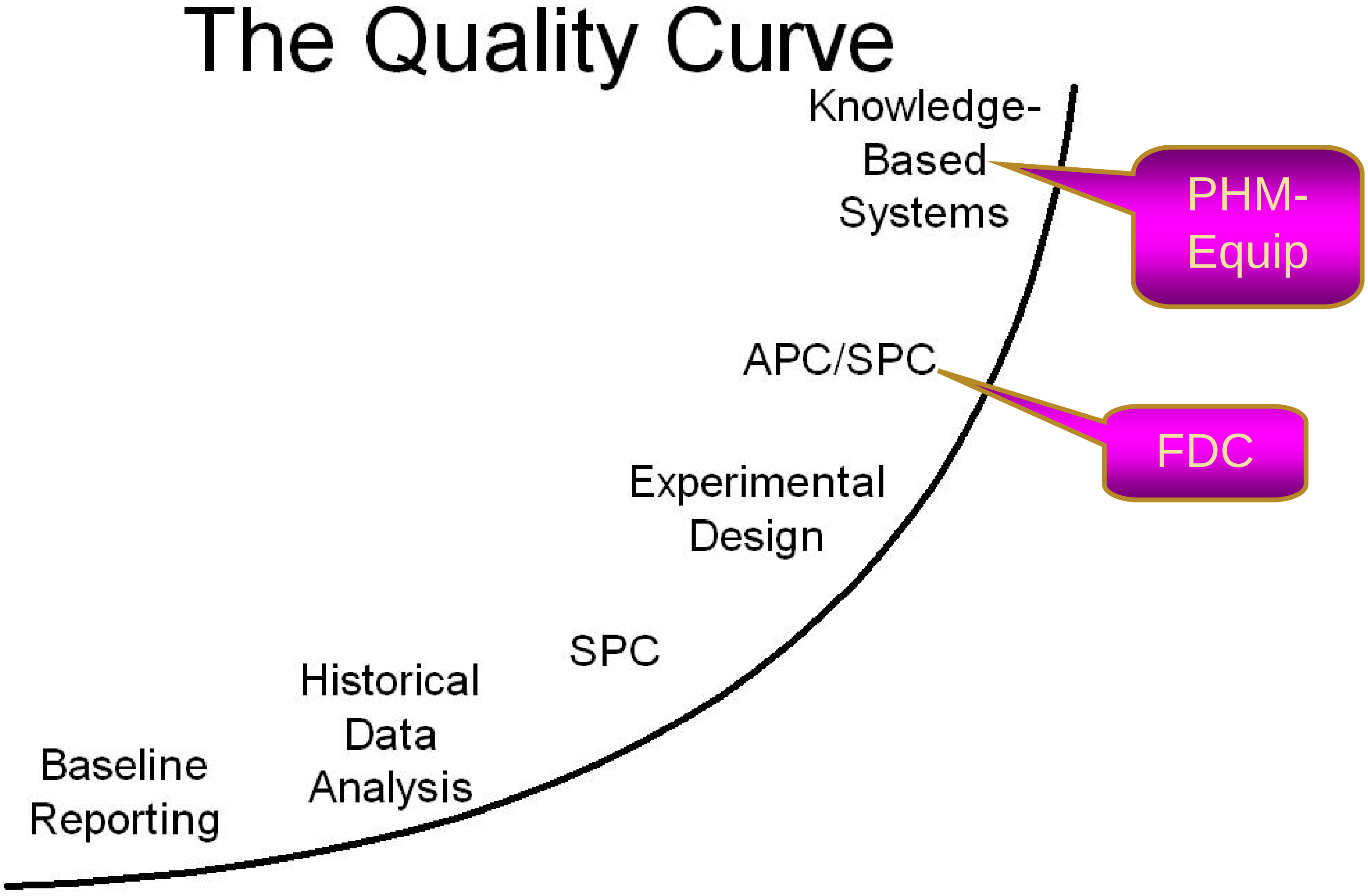


Benefits

- To eliminate false alarms
- To identify the potential impact to downstream metrology and/or E-Test parameter for any OOC
- Utilize engineering knowledge in FDC to have more accurate detection

APC/AEC 2005 / Intel Corporation "Weighted Fault Detection and Classification" Presenter: Mao, John

The Evolution of Quality Control



The Quality Curve

Baseline Reporting

Historical Data Analysis

SPC

Experimental Design

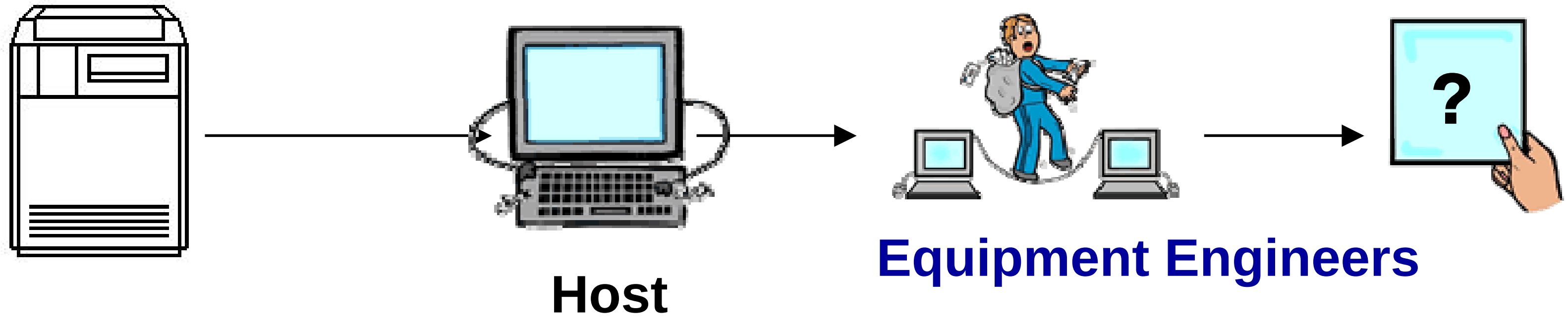
APC/SPC

Knowledge-Based Systems

PHM-Equip

FDC

CONVENTIONAL e-Diagnostic APPROACH



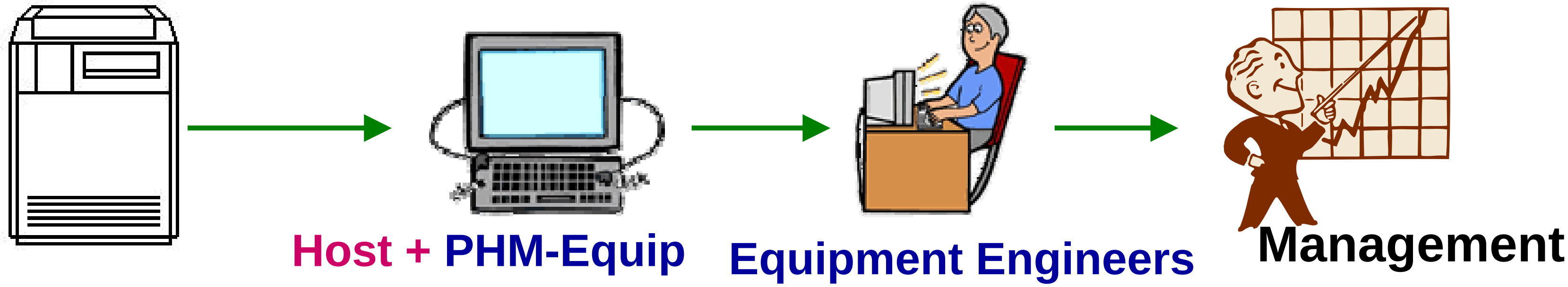
Host

Equipment Engineers

Slow Trouble Shooting Process

- **Opportunities of Human Errors:** Labor intensive and Time consuming
- **Passive Approach:** No knowledge sharing or self learning, lacking of predictive capability
- **Inconsistency:** Analysis results are human dependent
- **Cost of Resources:** Delay Time-to-Corrective Actions, Long training time for new engineers

AUTOMATED e-Diagnostic APPROACH



Host + PHM-Equip

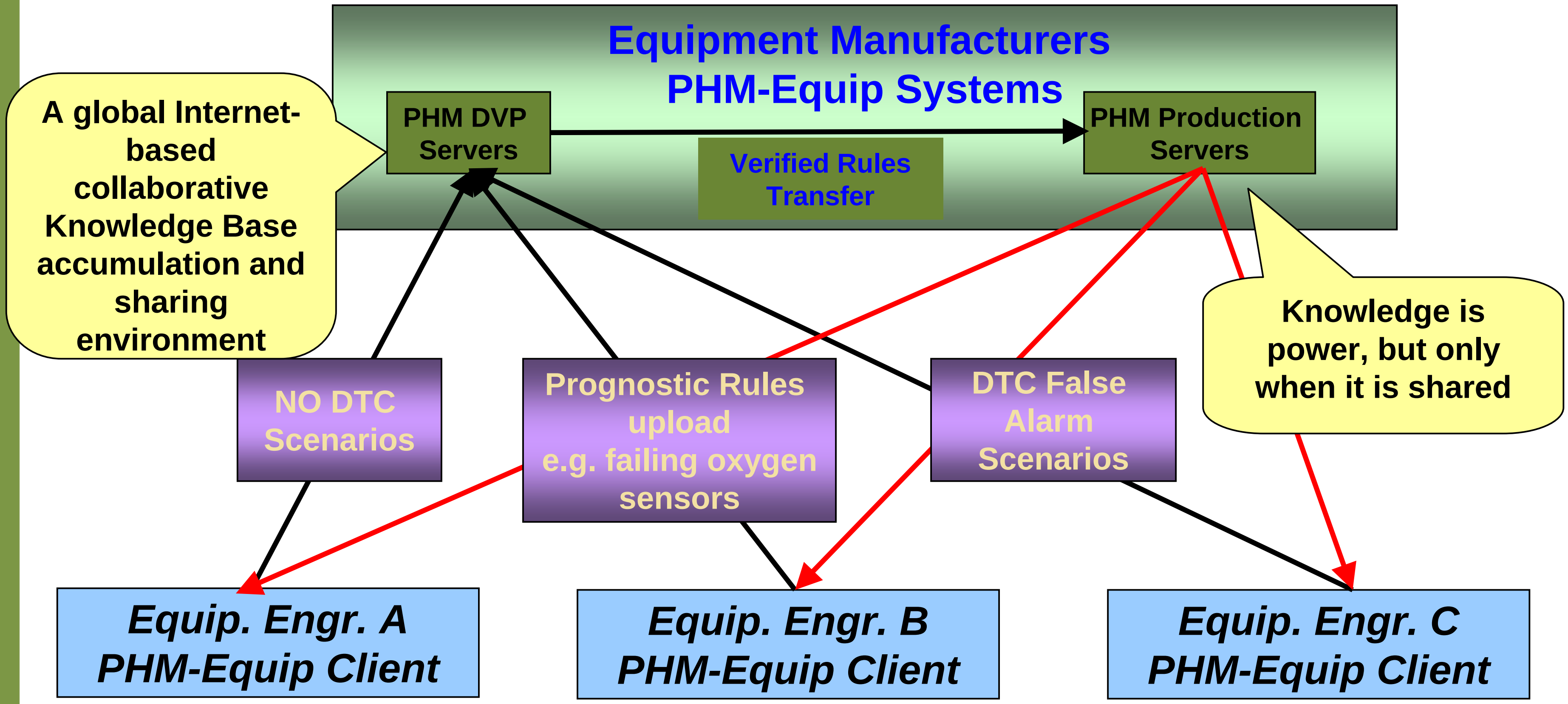
Equipment Engineers

Management

Enable Real Time Auto-Diagnostic

- **Reduce or Eliminate potential Human Errors:** Automated, Knowledge based Analysis
- **Feed Forward ↔ Feed Backward Proactive Approach:** Enable Knowledge Sharing, Self Correction, and providing Predictive Capability
- **Consistency:** Analysis results are based on Data and Knowledge
- **Saving Resources:** Fast Time-to-Corrective Actions, Shorten training time for new engineers

PHM-Equip Infrastructure



Equipment Manufacturers PHM-Equip Systems

PHM DVP Servers

PHM Production Servers

Verified Rules Transfer

A global Internet-based collaborative Knowledge Base accumulation and sharing environment

Knowledge is power, but only when it is shared

NO DTC Scenarios

Prognostic Rules upload e.g. failing oxygen sensors

DTC False Alarm Scenarios

Equip. Engr. A PHM-Equip Client

Equip. Engr. B PHM-Equip Client

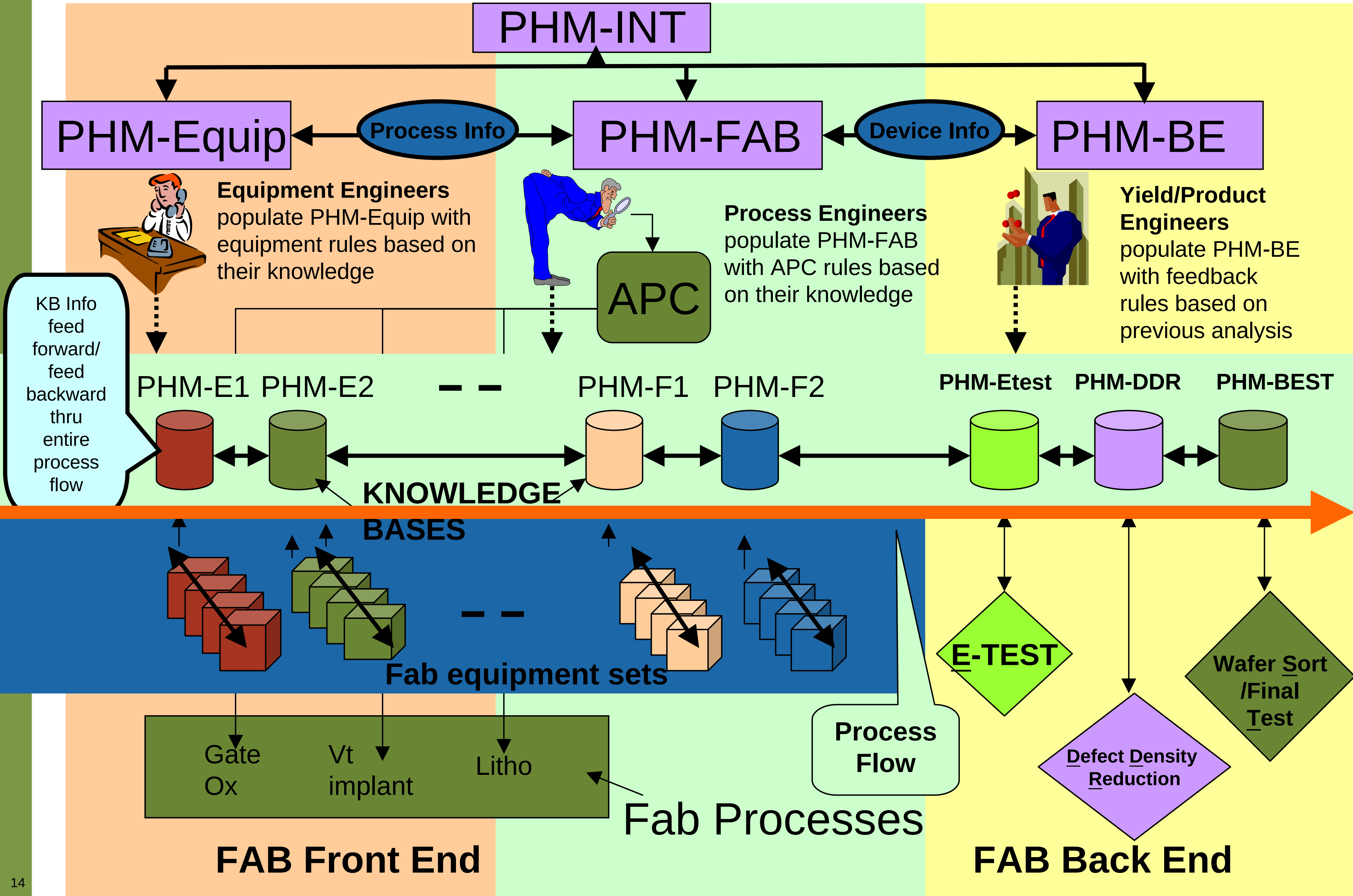
Equip. Engr. C PHM-Equip Client

◆PHM-Equip will help resolve **NO DTC (Diagnositc Troub-shooting Code)** problems

◆PHM-Equip will help resolve **DTC False Alarm** problems

◆PHM-Equip will accumulate **Prognostic Rules** from experienced equipment engineers

PHM-INT, PHM-Equipment, PHM-FAB & PHM-BE



PHM-INT

PHM-Equip

Process Info

PHM-FAB

Device Info

PHM-BE

Equipment Engineers populate PHM-Equip with equipment rules based on their knowledge

APC

Process Engineers populate PHM-FAB with APC rules based on their knowledge

Yield/Product Engineers populate PHM-BE with feedback rules based on previous analysis

KB Info feed forward/ feed backward thru entire process flow

PHM-E1 PHM-E2 – – PHM-F1 PHM-F2

PHM-Etest **PHM-DDR** **PHM-BEST**

KNOWLEDGE BASES

– –

Fab equipment sets

E-TEST

Wafer Sort /Final Test

Defect Density Reduction

Process Flow

Gate Ox

Vt implant

Litho

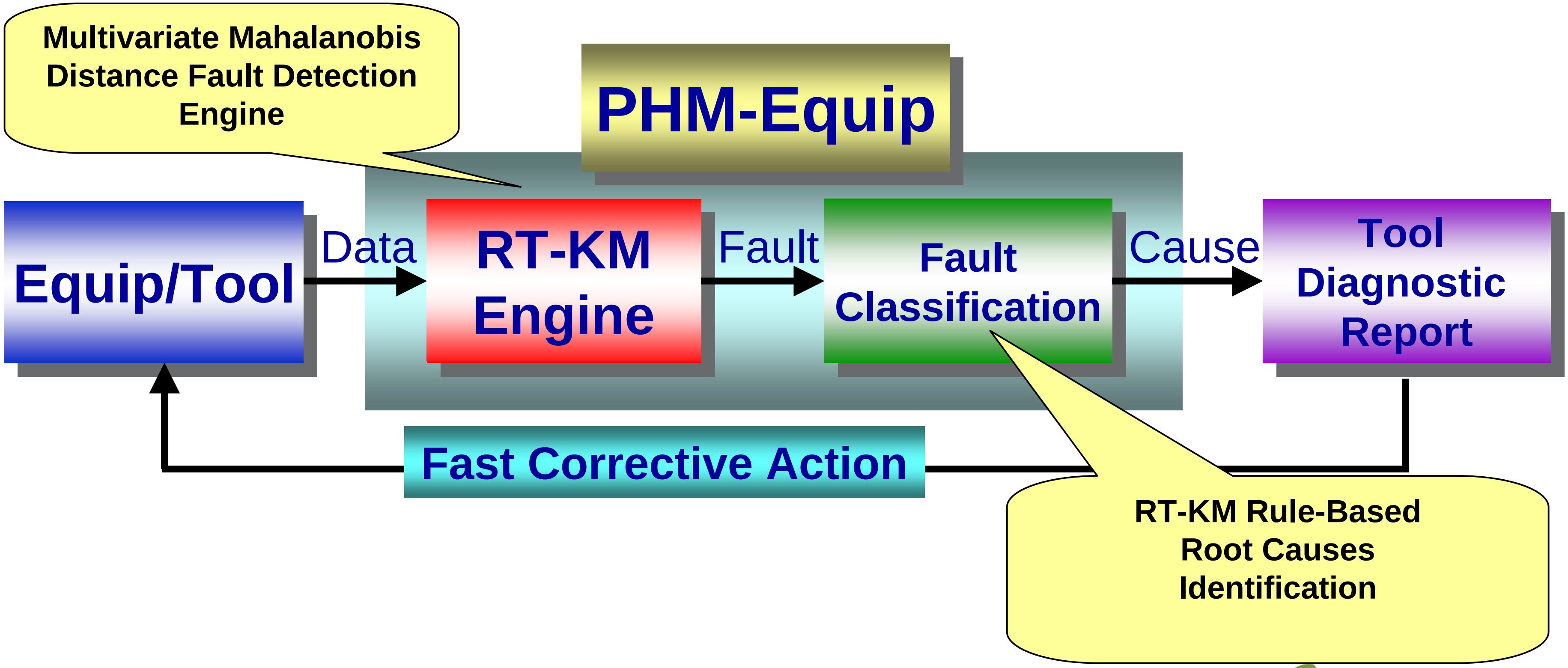
Fab Processes

FAB Front End

FAB Back End

PHM-Equip Architecture

- ❖ Western Electrical (WE) control charts with pattern recognition capability + Multivariate FDC to identify out of control tool parameters
- ❖ Advanced Real Time-Knowledge Management (RT-KM) Rule-based methodology automatically determine when an equipment fault occurs, what caused it, and how to correct it



Method: Mahalanobis Distance

- Introduced by Indian statistician P. C. Mahalanobis in 1936
- A distance measure based on correlations between the variables
- It meansures similarity/dissimilarity among observations.

*http://www.isid.ac.in/~library/pcm.htm, used with permission.

Method: Mahalanobis Distance

- Compute the covariance matrix *S* for observations of the group
- Mahalanobis distance is

$$D = \sqrt{(x-\mu)^T S^{-1} (x-\mu)}$$

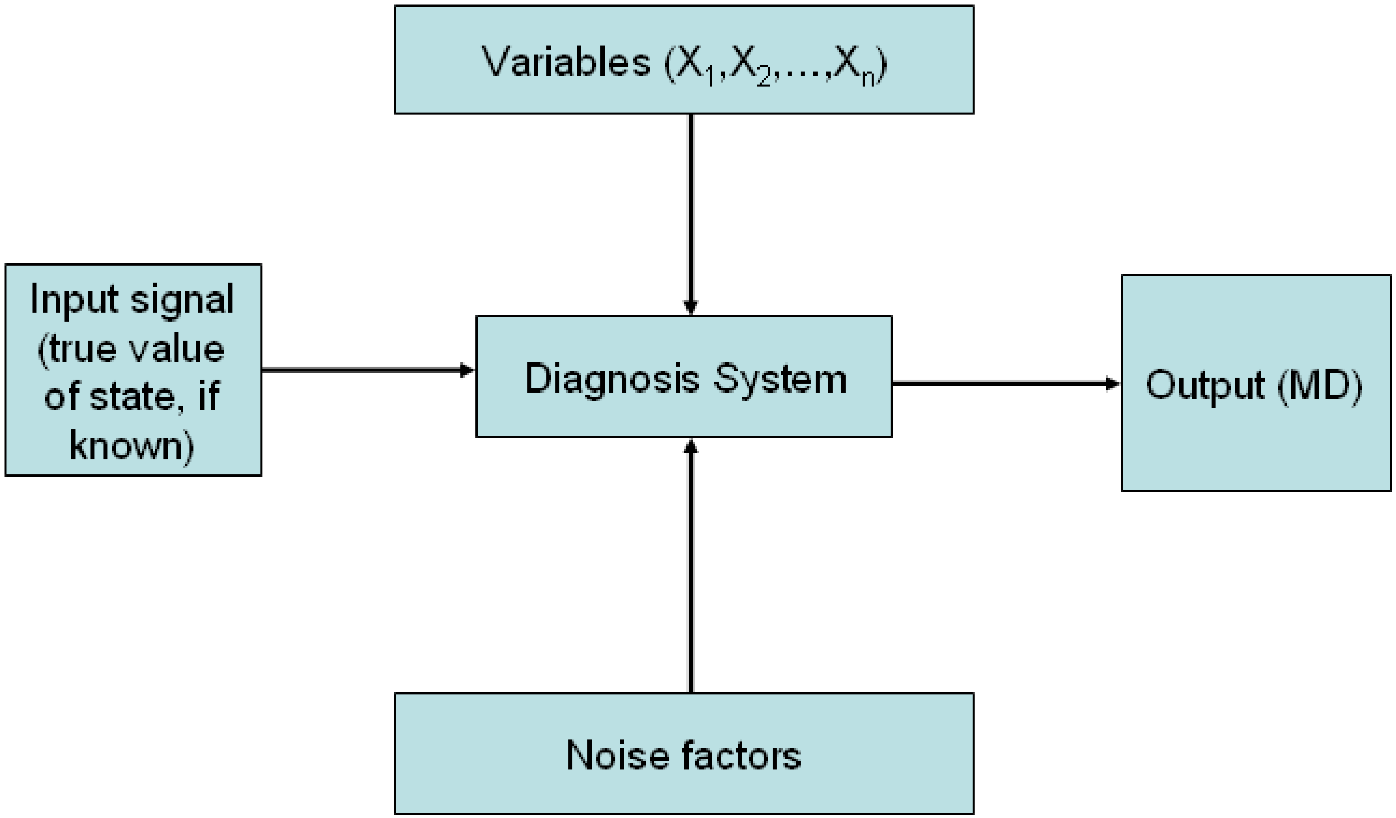
where μ is the mean of observations

- If covariance matrix *S* is the identity matrix then it is the same as Euclidean distance.
- If covariance matrix *S* is diagonal, then it is called normalized Euclidean distance:

Method: Mahalanobis-Taguchi System

This book integrates the principles of P. C. Mahalanobis and Genichi Taguchi. This photograph was taken at a rare occasion when these two were together at the Indian Statistical Institute, Calcutta, India, in 1954. Standing from left to right are P. C. Mahalanobis, Pandit Jawaharlal Nehru (then Indian Prime Minister), Walter A. Shewhart (known as the father of quality control), and Genichi Taguchi (shaking hands with the Prime Minister).

Method: Mahalanobis-Taguchi System A Multidimensional diagnosis system



Method: Mahalanobis-Taguchi System A Multidimensional diagnosis system

$$MD_j = D_j^{2} = (1/k) Z_{ij}^{T} C^{-1} Z_{ij} \qquad (1)$$

Where Z_i =standardized vector obtained by standardized values of $X_i \,(i = 1,2 \ldots k)$

$$Z_{ij} = (X_{ij} - \overline{X_i}) / S_i, i = 1,2,\ldots,k, j = 1,2,\ldots,n$$

$$\overline{X_i} = \frac{\sum_{j=1}^{n} X_{ij}}{n},$$

$$S_i = \sqrt{\frac{\sum_{j=1}^{n} (X_{ij} - \overline{X_i})^2}{n-1}},$$

Where X_{ij} =value of $i-th$ variable $j-th$ observation

Where S_i= standard deviations of i – th variable,

C^{-1} = the inverse of correlation matrix,

k = number of variables,

n = number of observations,

T = transpose of the standard vector.

PHM-Equip Examples: Data Source

Industrial example – TI etch data

- http://software.eigenvector.com/Data/Etch/index.html
- Consists of 21 variables from a LAM 9600 Metal Etcher over the course of etching 129 wafers
- The data consists of 108 normal wafers taken during 3 experiments
- 21 wafers with intentionally induced faults were taken during the same experiments (fault 12 has about half samples missing and is not included in this study)
- The experiments were run several weeks apart and data from different experiments has a different mean and somewhat different covariance structure

PHM-Equip Examples: Data Source

❖ Variables:

1. Time
2. Step Number
3. BCl3 Flow
4. Cl2 Flow
5. RF Btm Pwr
6. RF Btm Rfl Pwr
7. Endpt A
8. He Press
9. Pressure
10. RF Tuner
11. RF Load
12. RF Phase Err
13. RF Pwr
14. RF Impedance
15. TCP Tuner
16. TCP Phase Err
17. TCP Impedance
18. TCP Top Pwr
19. TCP Rfl Pwr
20. TCP Load
21. Vat Valve

(OES) Optical Emission Spectroscopy wavelength monitored

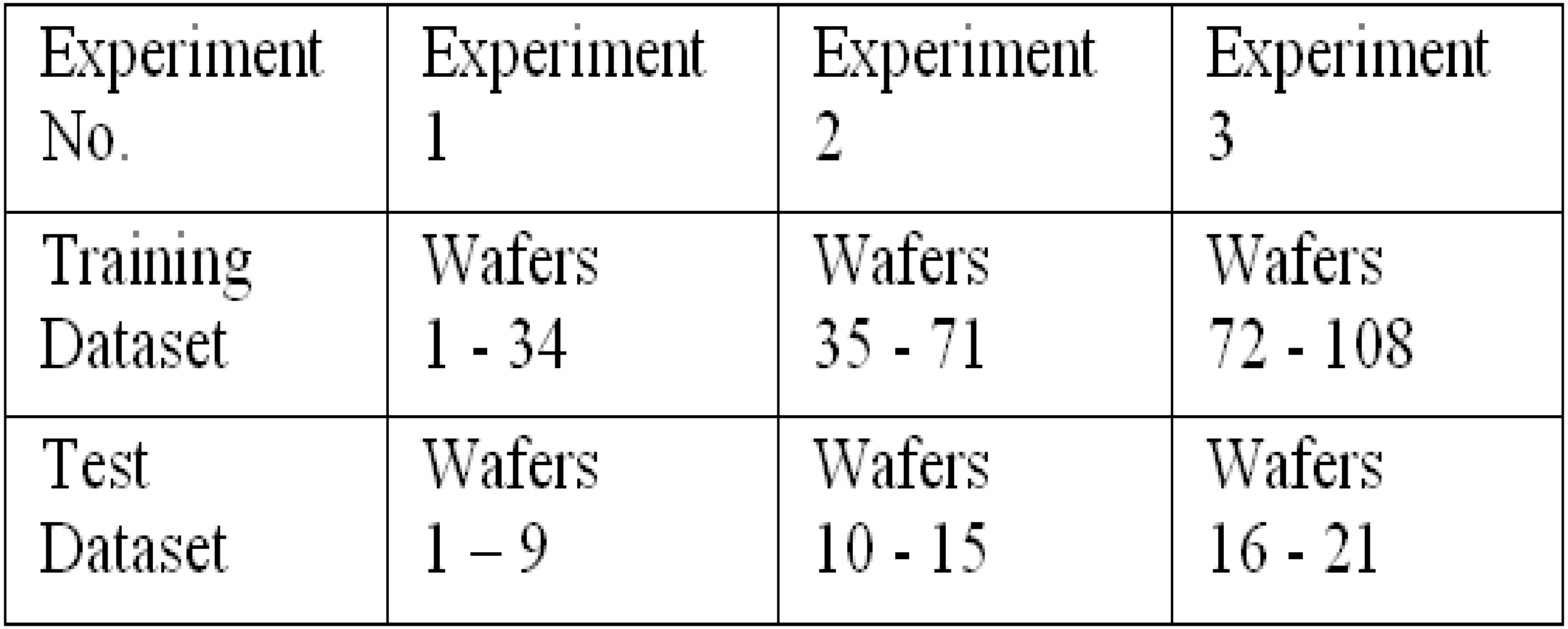
◆250 nm
◆261.8 nm
◆266.6 nm
◆272.2 nm
◆278.3 nm
◆284.6 nm
◆288.25 nm
◆…..
◆791.5 nm

❖ Faults:

1. TCP +50
2. RF -12
3. RF +10
4. Pr +3
5. TCP +10
6. BCl3 +5
7. Pr -2
8. Cl2 -5
9. He Chuck
10. TCP +30
11. Cl2 +5
12. BCl3 -5
13. Pr +2
14. TCP -20
15. TCP -15
16. Cl2 -10
17. RF -12
18. BCl3 +10
19. Pr +1
20. TCP +20

Results: Fault Detection

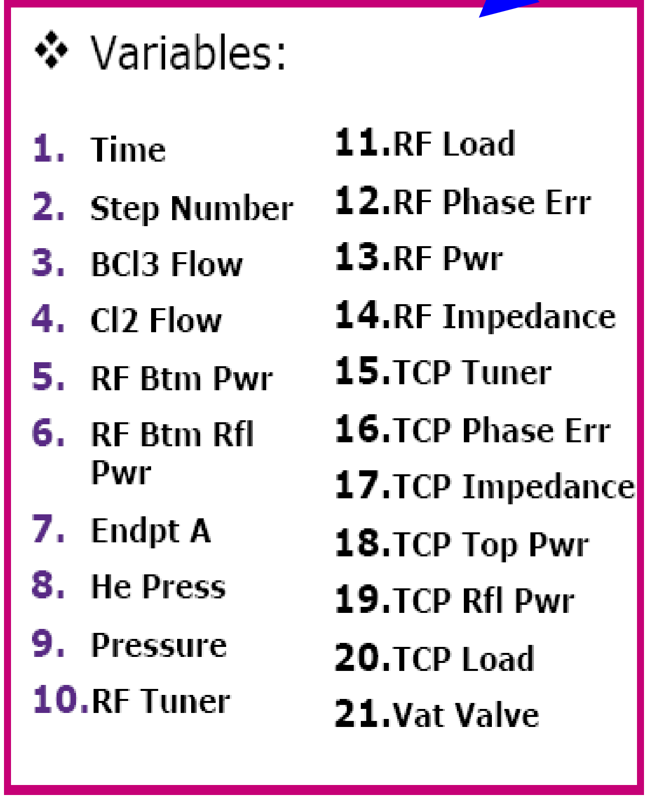
- Step 1: Define the Problem



Experiment No.	Experiment 1	Experiment 2	Experiment 3
Training Dataset	Wafers 1 - 34	Wafers 35 - 71	Wafers 72 - 108
Test Dataset	Wafers 1 – 9	Wafers 10 - 15	Wafers 16 - 21

Results: Fault Detection

- Step 2: Define Control/Response Variables



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(OES) Optical Emission Spectroscopy wavelength monitored

- ◆250 nm
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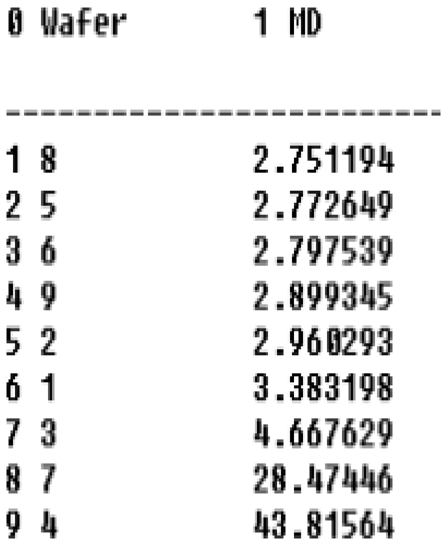
- ◆.....
- ◆791.5 nm

(MD) Mahalanobis Distance

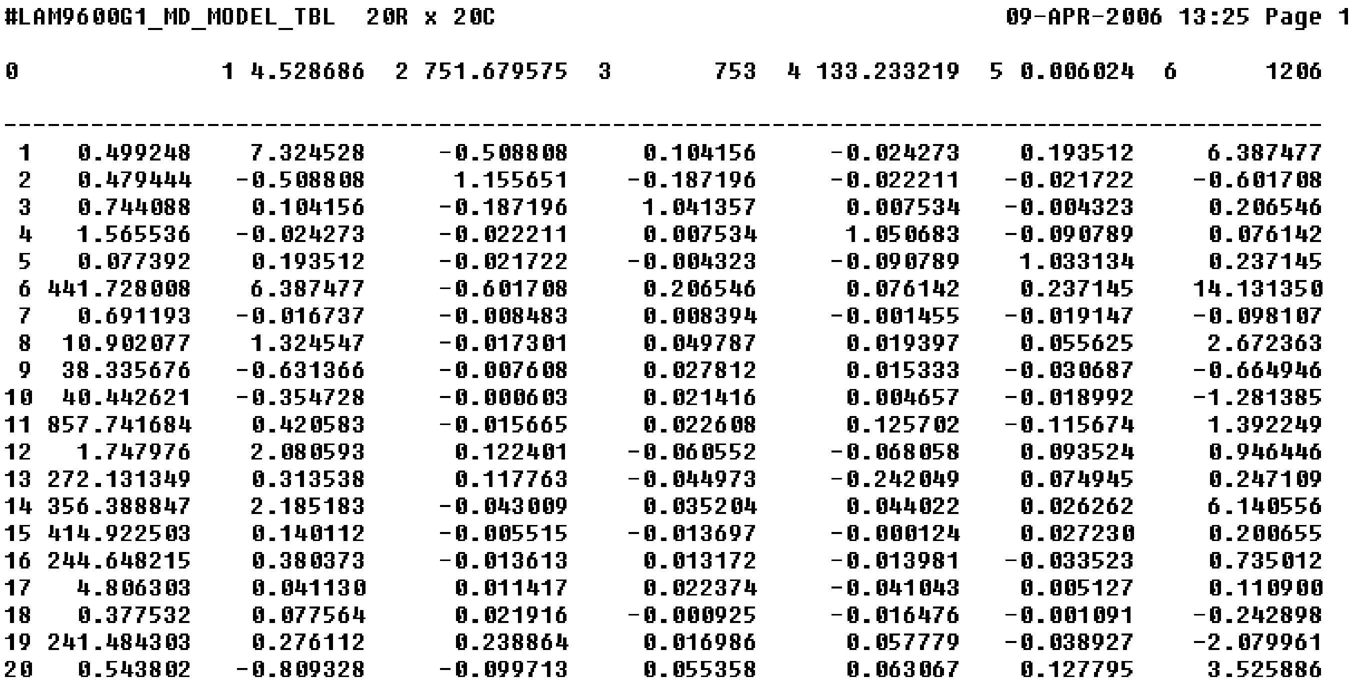


```
0 Wafer       1 MD

-------------------------
1 8           2.751194
2 5           2.772649
3 6           2.797539
4 9           2.899345
5 2           2.960293
6 1           3.383198
7 3           4.667629
8 7           28.47446
9 4           43.81564
```

Results: Fault Detection

- Step 3: Construct the “Full Model MTS Measurement Scale”

Note: The measurement scale is constructed by training datasets

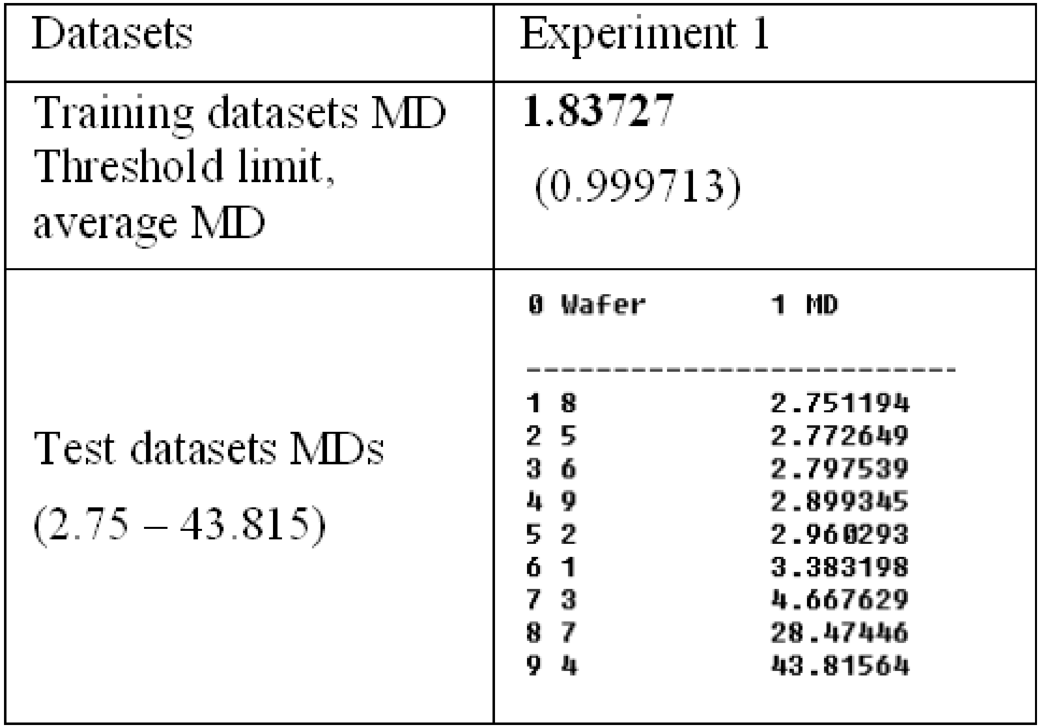


```
#LAM9600G1_MD_MODEL_TBL  20R x 20C                                   09-APR-2006 13:25 Page 1

0              1 4.528686  2 751.679575  3       753  4 133.233219  5 0.006024  6      1206

-------------------------------------------------------------------------------------------
 1   0.499248    7.324528     -0.508808     0.104156     -0.024273    0.193512     6.387477
 2   0.479444   -0.508808      1.155651    -0.187196     -0.022211   -0.021722    -0.601708
 3   0.744088    0.104156     -0.187196     1.041357      0.007534   -0.004323     0.206546
 4   1.565536   -0.024273     -0.022211     0.007534      1.050683   -0.090789     0.076142
 5   0.077392    0.193512     -0.021722    -0.004323     -0.090789    1.033134     0.237145
 6 441.728008    6.387477     -0.601708     0.206546      0.076142    0.237145    14.131350
 7   0.691193   -0.016737     -0.008483     0.008394     -0.001455   -0.019147    -0.098107
 8  10.902077    1.324547     -0.017301     0.049787      0.019397    0.055625     2.672363
 9  38.335676   -0.631366     -0.007608     0.027812      0.015333   -0.030687    -0.664946
10  40.442621   -0.354728     -0.000603     0.021416      0.004657   -0.018992    -1.281385
11 857.741684    0.420583     -0.015665     0.022608      0.125702   -0.115674     1.392249
12   1.747976    2.080593      0.122401    -0.060552     -0.068058    0.093524     0.946446
13 272.131349    0.313538      0.117763    -0.044973     -0.242049    0.074945     0.247109
14 356.388847    2.185183     -0.043009     0.035204      0.044022    0.026262     6.140556
15 414.922503    0.140112     -0.005515    -0.013697     -0.000124    0.027230     0.200655
16 244.648215    0.380373     -0.013613     0.013172     -0.013981   -0.033523     0.735012
17   4.806303    0.041130      0.011417     0.022374     -0.041043    0.005127     0.110900
18   0.377532    0.077564      0.021916    -0.000925     -0.016476   -0.001091    -0.242898
19 241.484303    0.276112      0.238864     0.016986      0.057779   -0.038927    -2.079961
20   0.543802   -0.809328     -0.099713     0.055358      0.063067    0.127795     3.525886
```

Results: Fault Detection

- Step 4: Validate the ability of measurement scale

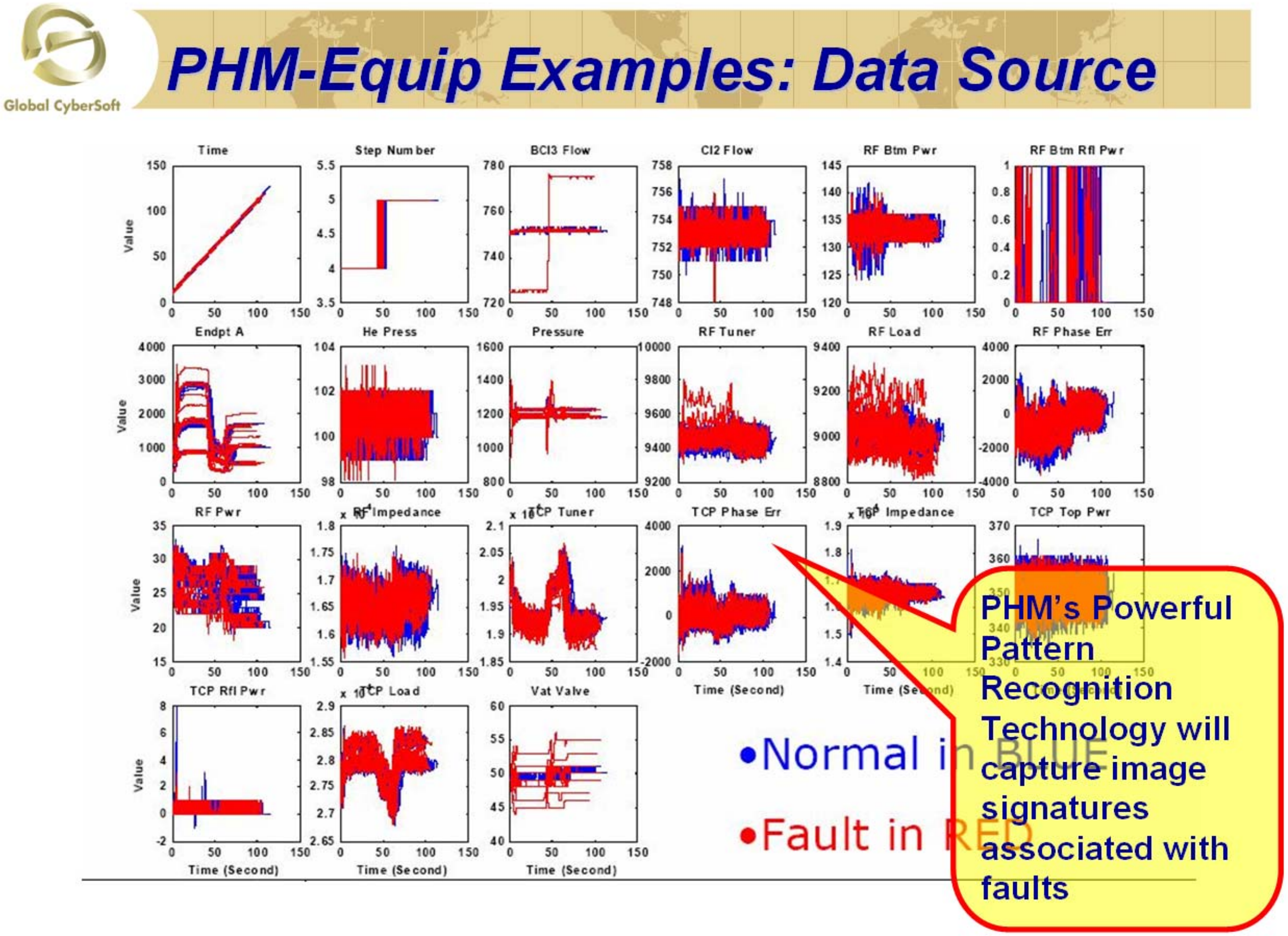
Note: the capability of measurement scale is demonstrated by test datasets.



Datasets	Experiment 1
Training datasets MD Threshold limit, average MD	**1.83727** (0.999713)
Test datasets MDs (2.75 – 43.815)	0 Wafer 1 MD -------------------------- 1 8 2.751194 2 5 2.772649 3 6 2.797539 4 9 2.899345 5 2 2.960293 6 1 3.383198 7 3 4.667629 8 7 28.47446 9 4 43.81564

Results: Fault Classification

Method: Distinguish the signal pattern shift of each variable between the test dataset and the model



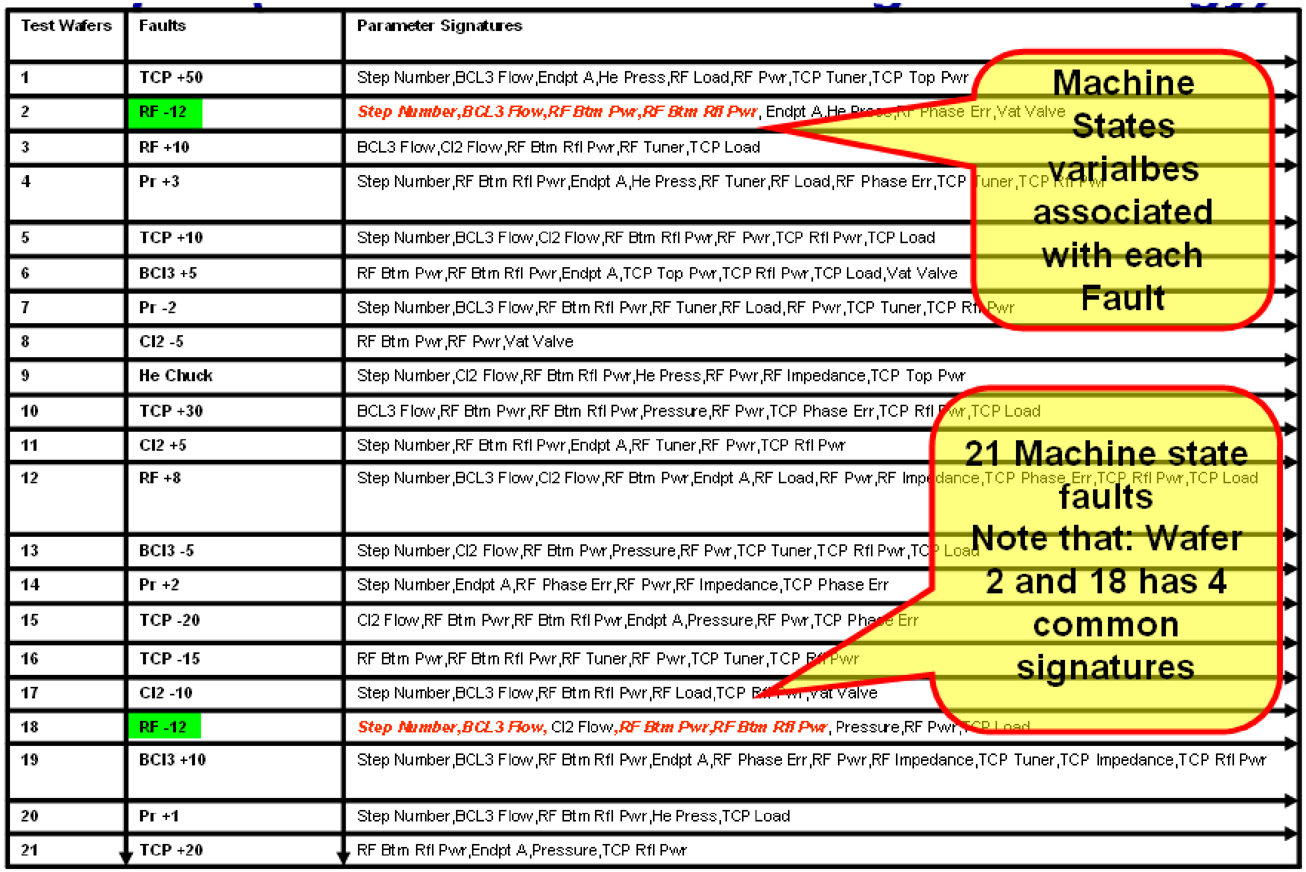
PHM-Equip Examples: Data Source

- Normal in BLUE
- Fault in RED

PHM's Powerful Pattern Recognition Technology will capture image signatures associated with faults

Results: Fault Classification

Results: Test wafer 2 and test wafer 18 have the same four machine state variables associated with the RF-12 system fault.

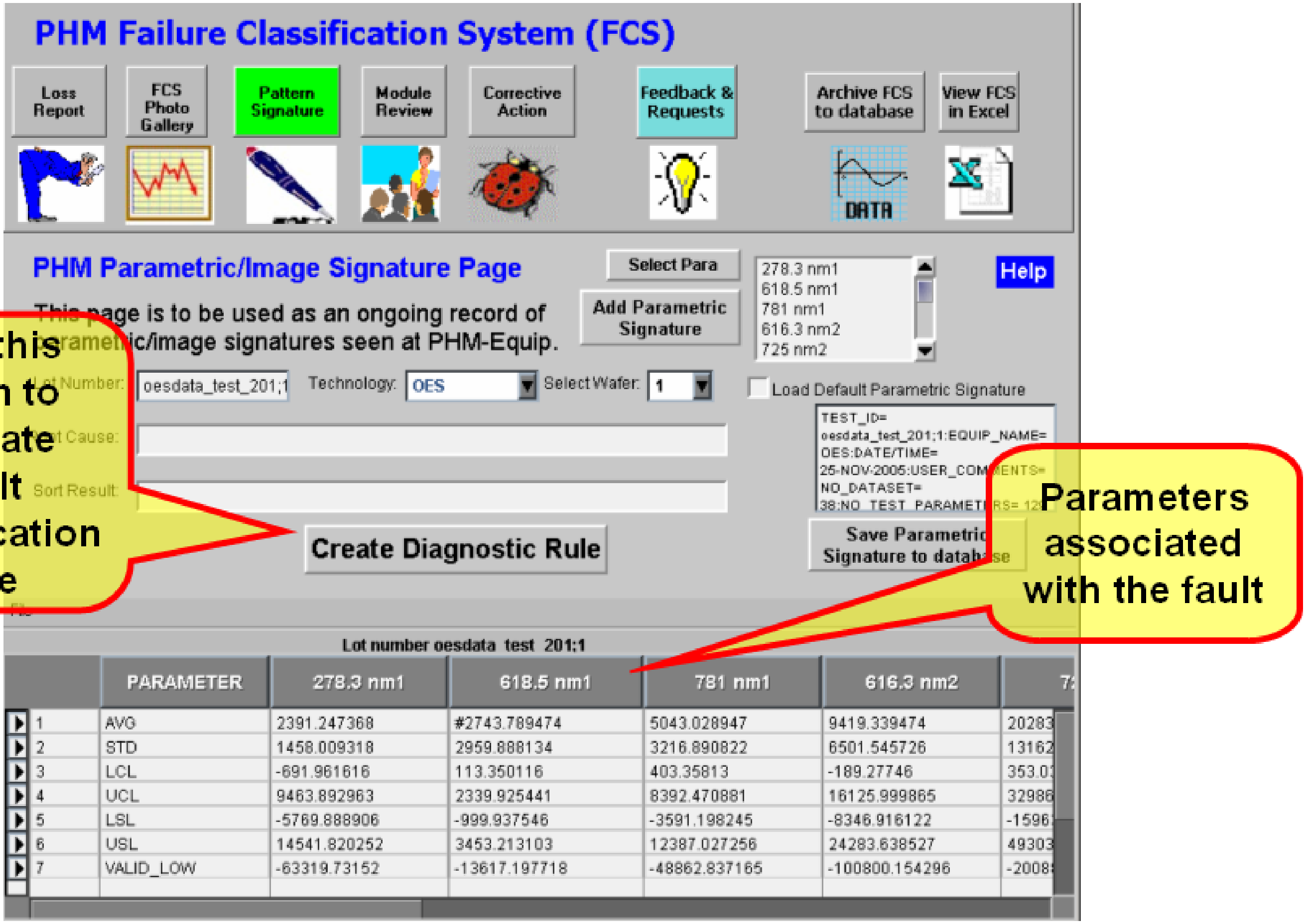


Test Wafers	Faults	Parameter Signatures
1	TCP +50	Step Number,BCL3 Flow,Endpt A,He Press,RF Load,RF Pwr,TCP Tuner,TCP Top Pwr
2	RF -12	**Step Number,BCL3 Flow,RF Btm Pwr,RF Btm Rfl Pwr**, Endpt A,He Press,RF Phase Err,Vat Valve
3	RF +10	BCL3 Flow,Cl2 Flow,RF Btm Rfl Pwr,RF Tuner,TCP Load
4	Pr +3	Step Number,RF Btm Rfl Pwr,Endpt A,He Press,RF Tuner,RF Load,RF Phase Err,TCP Tuner,TCP Rfl Pwr
5	TCP +10	Step Number,BCL3 Flow,Cl2 Flow,RF Btm Rfl Pwr,RF Pwr,TCP Rfl Pwr,TCP Load
6	BCl3 +5	RF Btm Pwr,RF Btm Rfl Pwr,Endpt A,TCP Top Pwr,TCP Rfl Pwr,TCP Load,Vat Valve
7	Pr -2	Step Number,BCL3 Flow,RF Btm Rfl Pwr,RF Tuner,RF Load,RF Pwr,TCP Tuner,TCP Rfl Pwr
8	Cl2 -5	RF Btm Pwr,RF Pwr,Vat Valve
9	He Chuck	Step Number,Cl2 Flow,RF Btm Rfl Pwr,He Press,RF Pwr,RF Impedance,TCP Top Pwr
10	TCP +30	BCL3 Flow,RF Btm Pwr,RF Btm Rfl Pwr,Pressure,RF Pwr,TCP Phase Err,TCP Rfl Pwr,TCP Load
11	Cl2 +5	Step Number,RF Btm Rfl Pwr,Endpt A,RF Tuner,RF Pwr,TCP Rfl Pwr
12	RF +8	Step Number,BCL3 Flow,Cl2 Flow,RF Btm Pwr,Endpt A,RF Load,RF Pwr,RF Impedance,TCP Phase Err,TCP Rfl Pwr,TCP Load
13	BCl3 -5	Step Number,Cl2 Flow,RF Btm Pwr,Pressure,RF Pwr,TCP Tuner,TCP Rfl Pwr,TCP Load
14	Pr +2	Step Number,Endpt A,RF Phase Err,RF Pwr,RF Impedance,TCP Phase Err
15	TCP -20	Cl2 Flow,RF Btm Pwr,RF Btm Rfl Pwr,Endpt A,Pressure,RF Pwr,TCP Phase Err
16	TCP -15	RF Btm Pwr,RF Btm Rfl Pwr,RF Tuner,RF Pwr,TCP Tuner,TCP Rfl Pwr
17	Cl2 -10	Step Number,BCL3 Flow,RF Btm Rfl Pwr,RF Load,TCP Rfl Pwr,Vat Valve
18	RF -12	**Step Number,BCL3 Flow,** Cl2 Flow,**RF Btm Pwr,RF Btm Rfl Pwr**, Pressure,RF Pwr,TCP Load
19	BCl3 +10	Step Number,BCL3 Flow,RF Btm Rfl Pwr,Endpt A,RF Phase Err,RF Pwr,RF Impedance,TCP Tuner,TCP Impedance,TCP Rfl Pwr
20	Pr +1	Step Number,BCL3 Flow,RF Btm Rfl Pwr,He Press,TCP Load
21	TCP +20	RF Btm Rfl Pwr,Endpt A,Pressure,TCP Rfl Pwr

Machine States varialbes associated with each Fault

21 Machine state faults
Note that: Wafer 2 and 18 has 4 common signatures

Create Diagnostic Rule from pattern signature



PHM Parametric/Image Signature Page

This page is to be used as an ongoing record of parametric/image signatures seen at PHM-Equip.

278.3 nm1
618.5 nm1
781 nm1
616.3 nm2
725 nm2

Lot Number: oesdata_test_201;1
Technology: OES
Select Wafer: 1
☐ Load Default Parametric Signature

Cause:

Sort Result:

```
TEST_ID=
oesdata_test_201;1:EQUIP_NAME=
OES:DATE/TIME=
25-NOV-2005:USER_COMMENTS=
NO_DATASET=
38:NO_TEST_PARAMETERS= 12
```

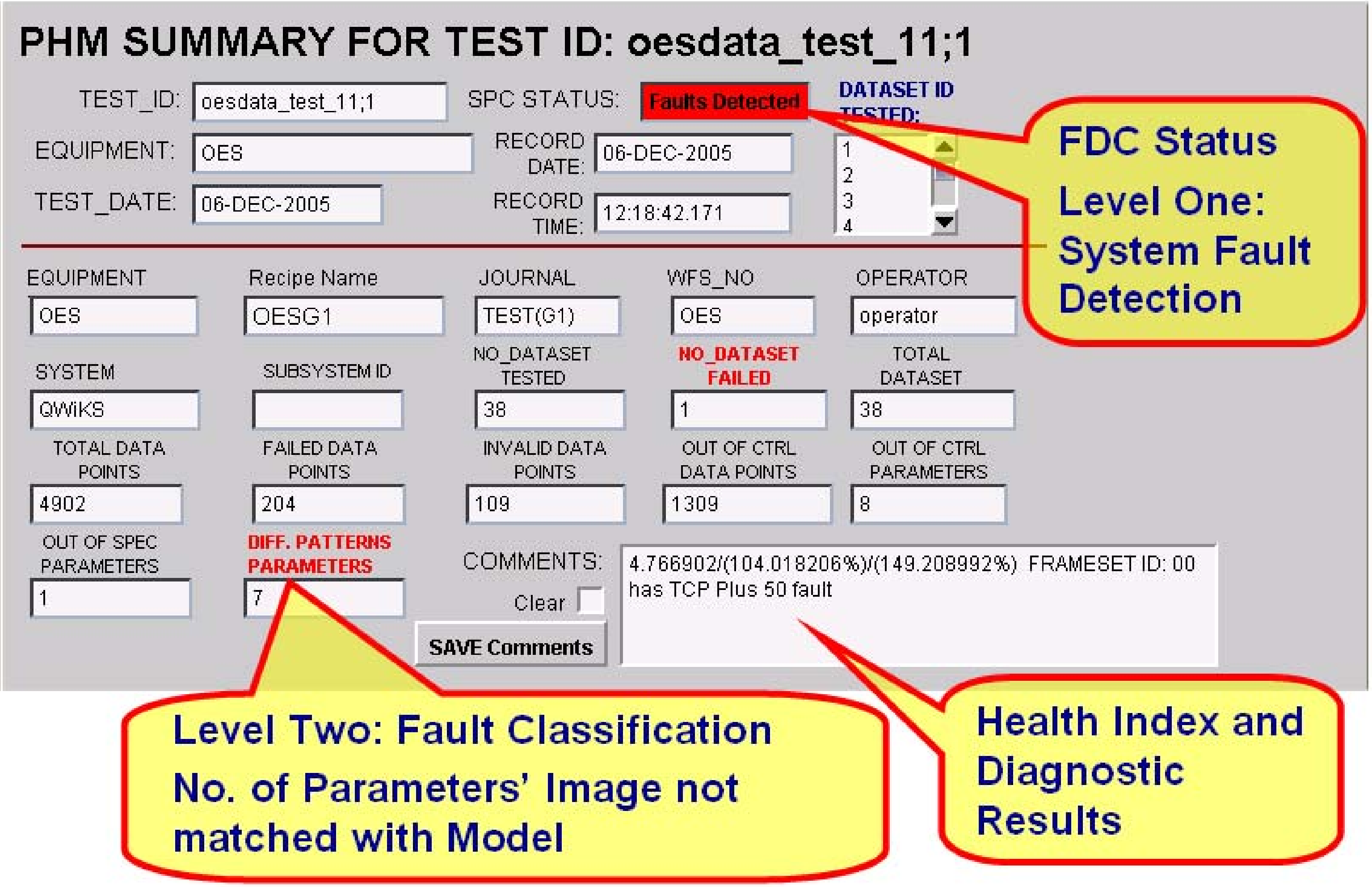
Lot number oesdata test 201;1

	PARAMETER	278.3 nm1	618.5 nm1	781 nm1	616.3 nm2	7
1	AVG	2391.247368	#2743.789474	5043.028947	9419.339474	20283
2	STD	1458.009318	2959.888134	3216.890822	6501.545726	13162
3	LCL	-691.961616	113.350116	403.35813	-189.27746	353.0
4	UCL	9463.892963	2339.925441	8392.470881	16125.999865	32986
5	LSL	-5769.888906	-999.937546	-3591.198245	-8346.916122	-1596
6	USL	14541.820252	3453.213103	12387.027256	24283.638527	49303
7	VALID_LOW	-63319.73152	-13617.197718	-48862.837165	-100800.154296	-2008

Click this button to generate Fault Classification Rule

Parameters associated with the fault

PHM Fault Detection and Classification Summary



PHM SUMMARY FOR TEST ID: oesdata_test_11;1

TEST_ID: oesdata_test_11;1
SPC STATUS: Faults Detected
DATASET ID TESTED: 1 2 3 4
EQUIPMENT: OES
RECORD DATE: 06-DEC-2005
TEST_DATE: 06-DEC-2005
RECORD TIME: 12:18:42.171

EQUIPMENT	Recipe Name	JOURNAL	WFS_NO	OPERATOR
OES	OESG1	TEST(G1)	OES	operator
SYSTEM	SUBSYSTEM ID	NO_DATASET TESTED	NO_DATASET FAILED	TOTAL DATASET
QWiKS		38	1	38
TOTAL DATA POINTS	FAILED DATA POINTS	INVALID DATA POINTS	OUT OF CTRL DATA POINTS	OUT OF CTRL PARAMETERS
4902	204	109	1309	8
OUT OF SPEC PARAMETERS	DIFF. PATTERNS PARAMETERS			
1	7			

COMMENTS: 4.766902/(104.018206%)/(149.208992%) FRAMESET ID: 00 has TCP Plus 50 fault

Clear ☐

FDC Status

Level One: System Fault Detection

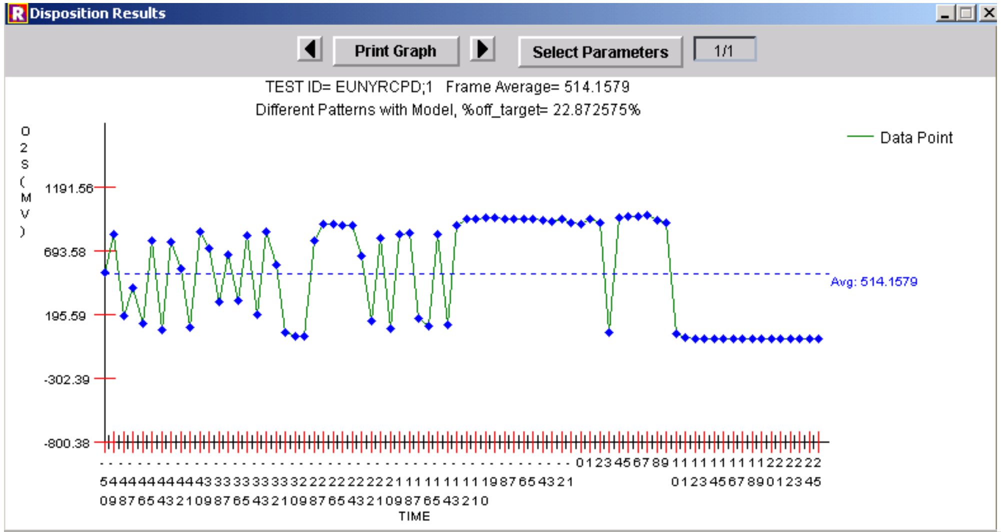
Level Two: Fault Classification

No. of Parameters' Image not matched with Model

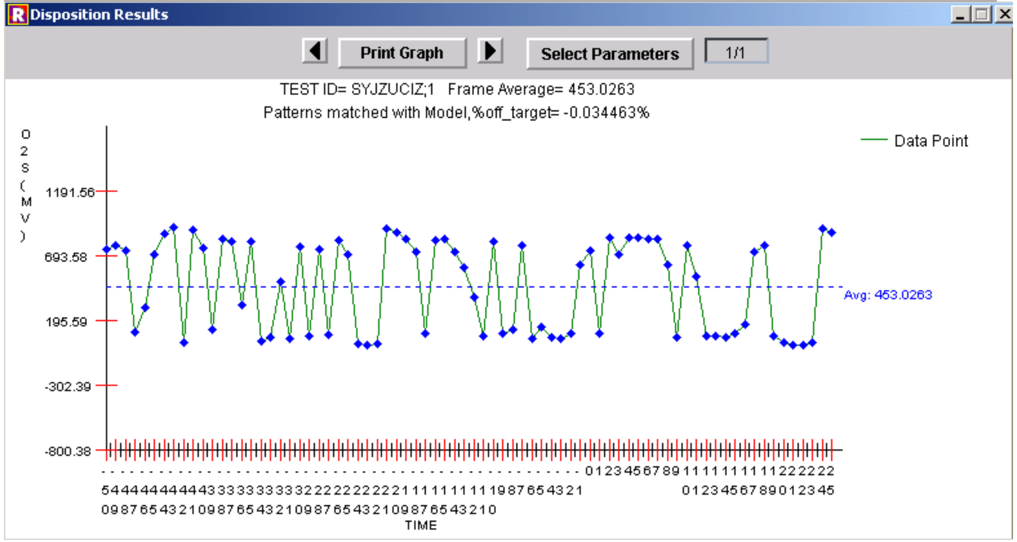
Health Index and Diagnostic Results

Promote Predictive Maintenance

Example of Prognostic Rule for oxygen sensor

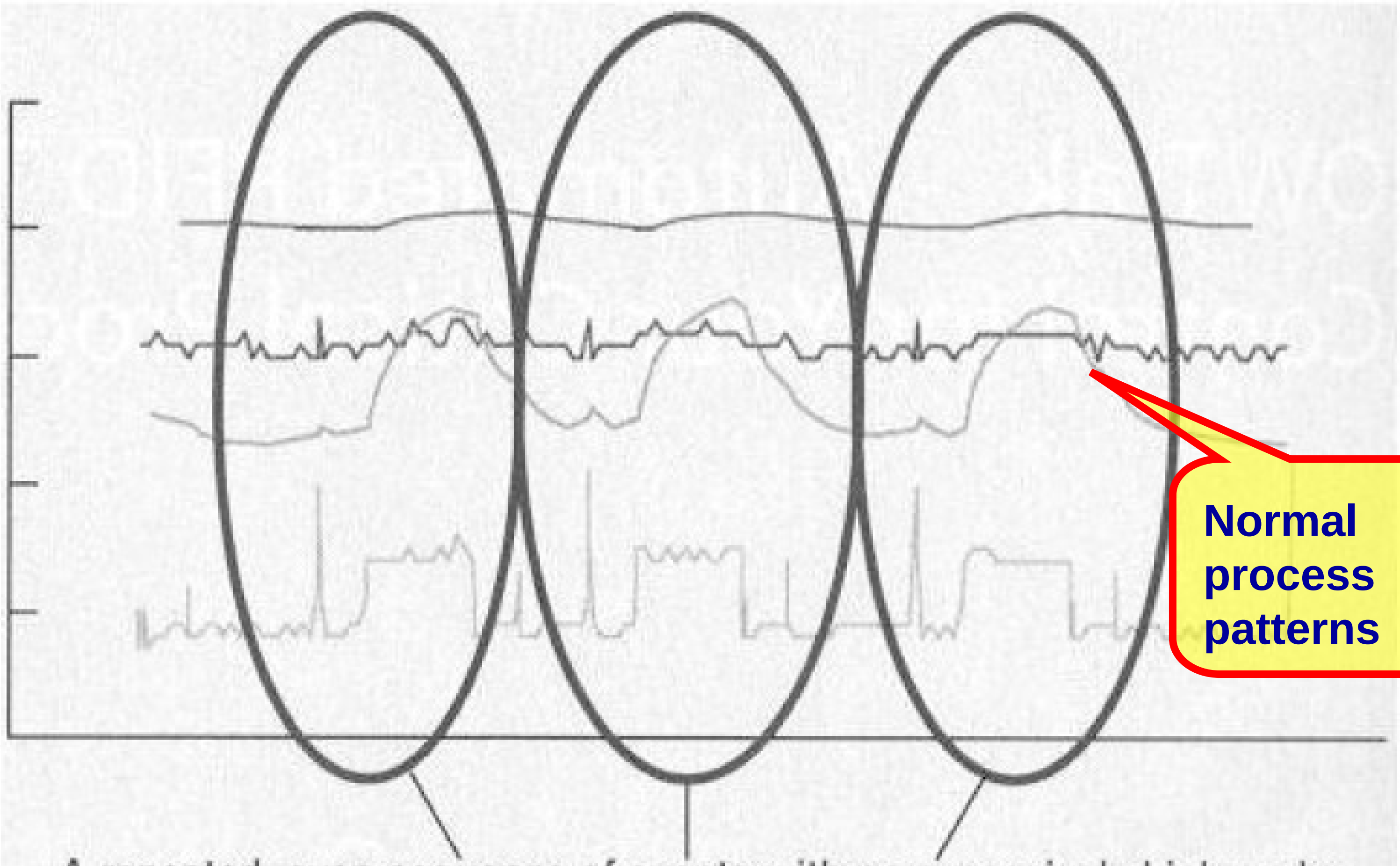


TEST ID= EUNYRCPD;1 Frame Average= 514.1579
Different Patterns with Model, %off_target= 22.872575%



TEST ID= SYJZUCIZ;1 Frame Average= 453.0263
Patterns matched with Model,%off_target= -0.034463%

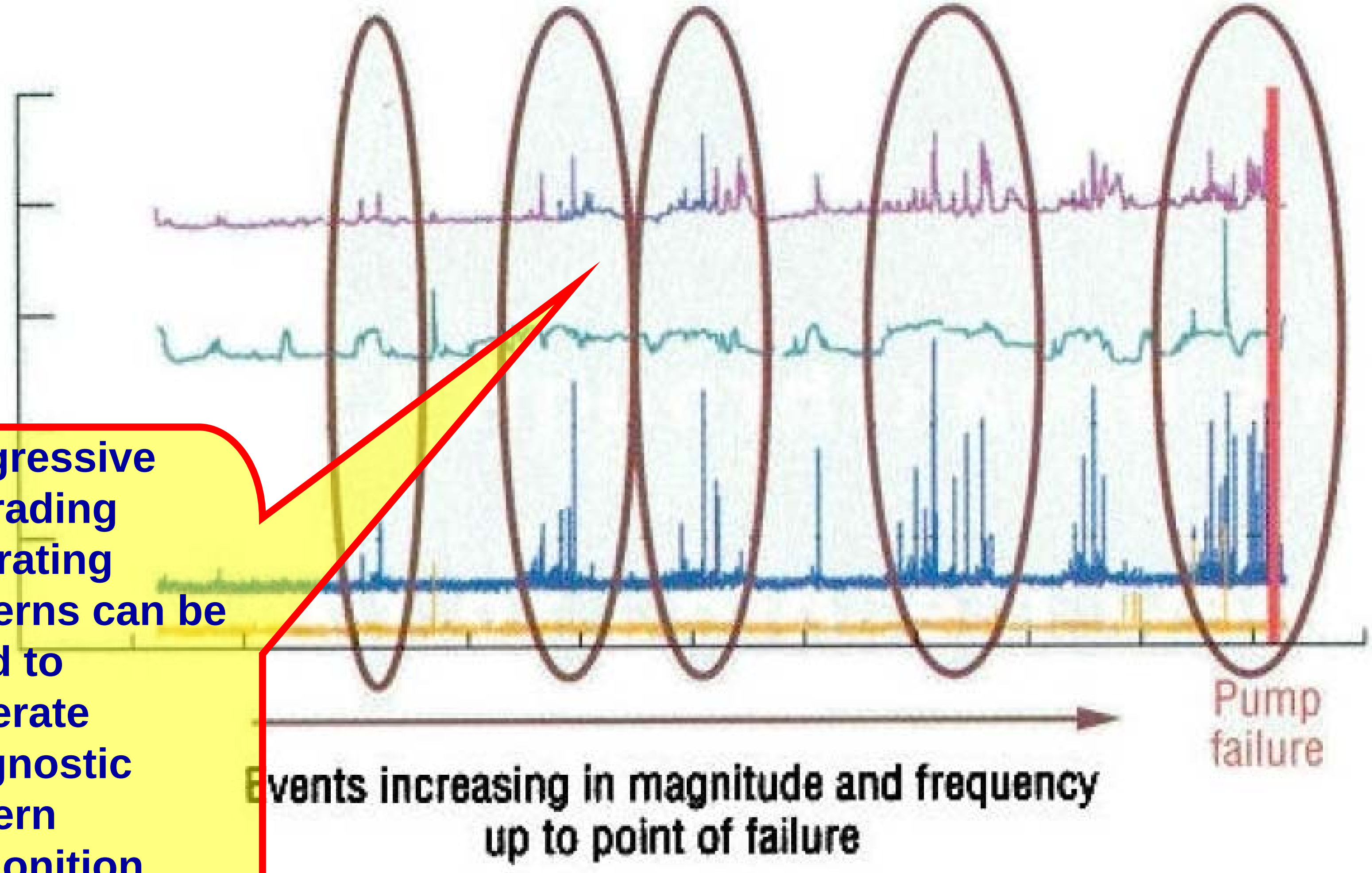
PHM-Equip Example: Diagnostic Results



A repeated, even sequence of events with no excessively high peaks suggests a good pump running normal process patterns.

Normal process patterns

PHM-Equip Example: Diagnostic Results

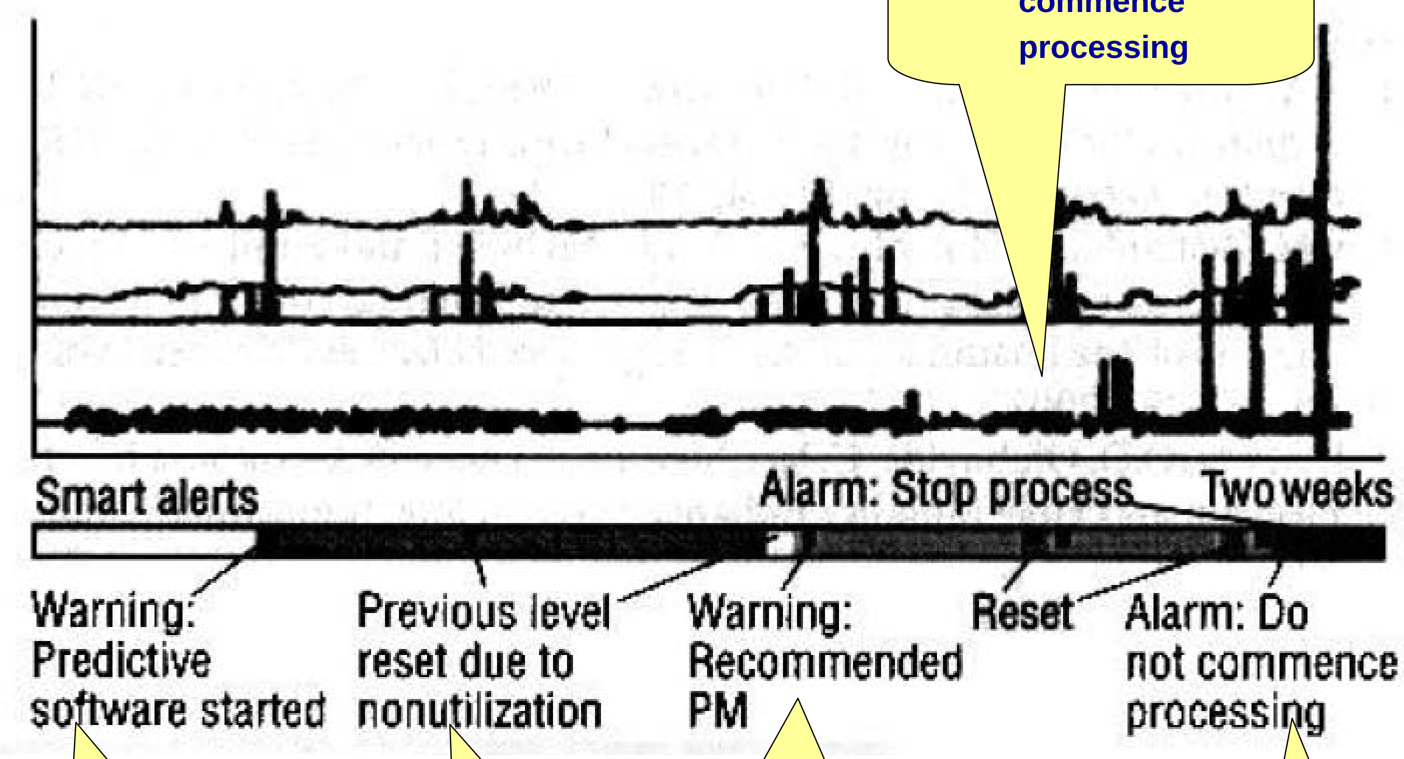


Pump failure

Events increasing in magnitude and frequency up to point of failure

Progressive degrading Operating patterns can be used to generate prognostic pattern recgonition rules

State-based Warning System



4. Do not commence processing

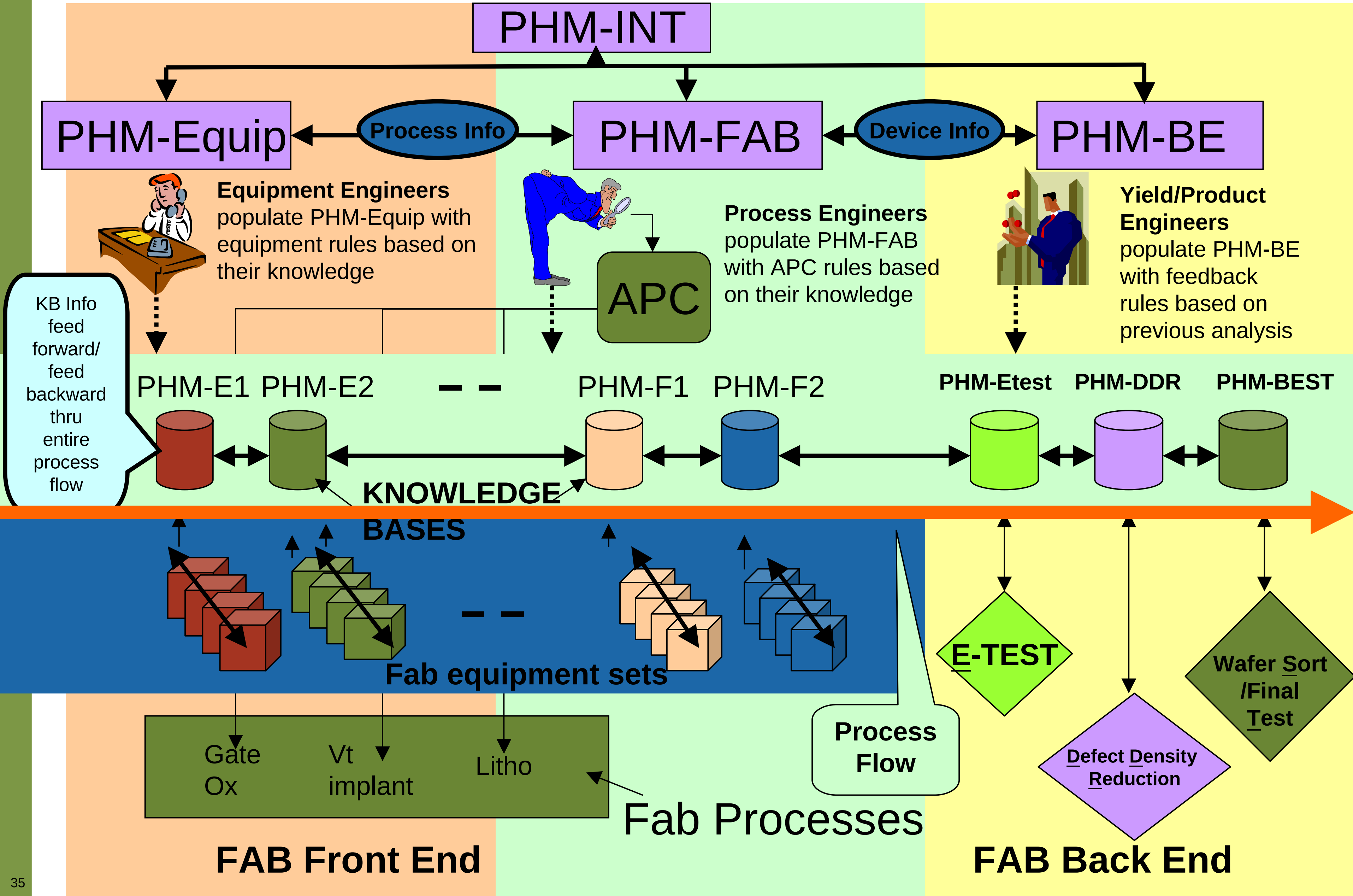
1. Normal

2. Predictive Monitoring started

3. Recommand preventive maintenance (PM) in 48 hr
Monitoring started

5. Stop Processing

PHM-INT, PHM-Equipment, PHM-FAB & PHM-BE



Equipment Engineers populate PHM-Equip with equipment rules based on their knowledge

Process Engineers populate PHM-FAB with APC rules based on their knowledge

Yield/Product Engineers populate PHM-BE with feedback rules based on previous analysis

PHM VALUE PROPOSITION

- Provide Predictive Equipment Maintenance & Diagnostics
- Correct Problems before failure occurs
- Real time process/tool/equipment health feedback
- Pinpoints miss processing/equipment malfunction steps
- Diagnostic report feeds backward
- Diagnostic report feeds forward
- Knowledge reusable, never lost