

# MATLAB EXPO 2019

## APM기반의 자기진단:

반도체공정용 진공펌프 상태진단의 새로운 지평

한국표준과학연구원 / 역학센터  
정완섭

**KRISs**



## 목차

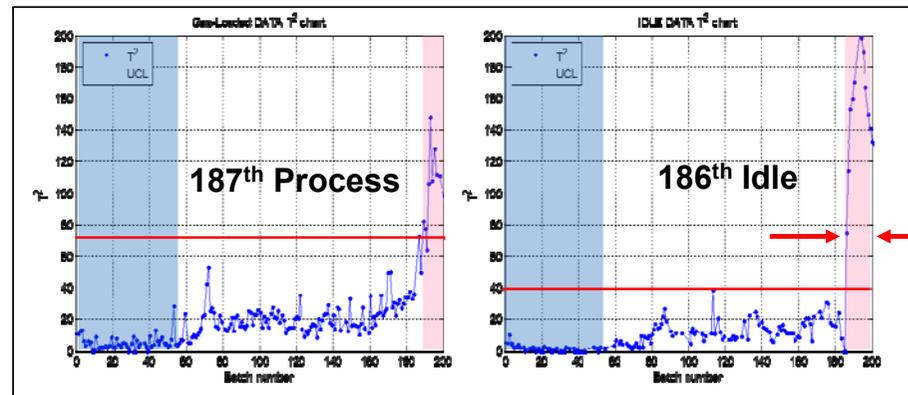
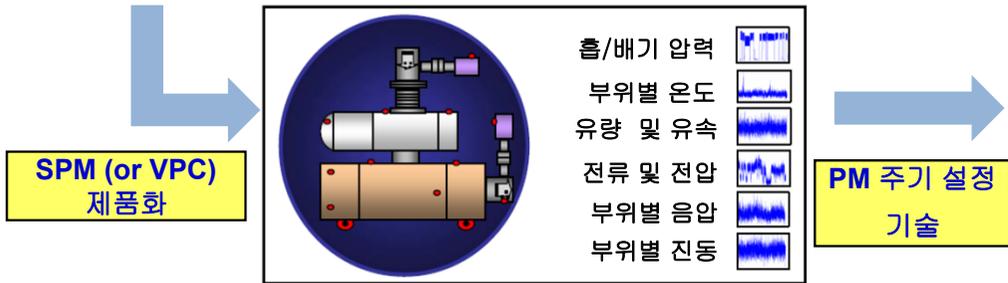
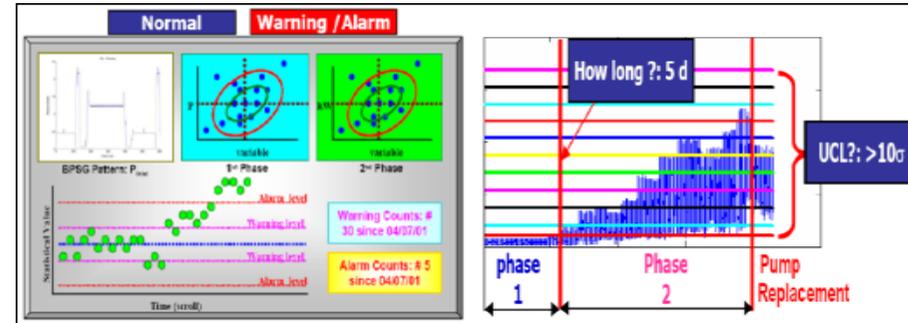
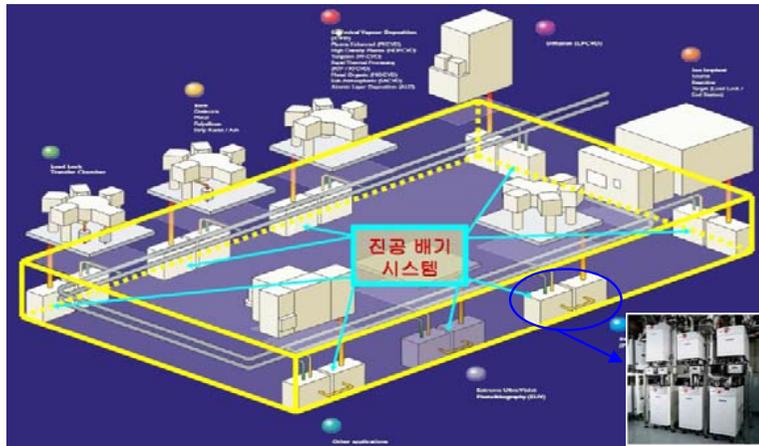
1. 회사 및 발표자 소개 (Introduction to Organization and Business)
2. 국책과제 개요 (Project Overview)
3. 진공펌프 상태진단의 기술적 과제 (Technical Challenges of Diagnosis of Vacuum Pumps)
4. APM 기반의 자기진단 기술 (APM-Based Self-Diagnostics for Vacuum Pumps)
5. Matlab 코드 체계 (Matlab Code Structure of APM-Based Self-Diagnostics )
6. 진공펌프 상태진단 및 예지 결과 예시 (Illustrations of Diagnostics of Vacuum Pumps)
7. 결론 (Concluding Remarks)

# 발표자 소개



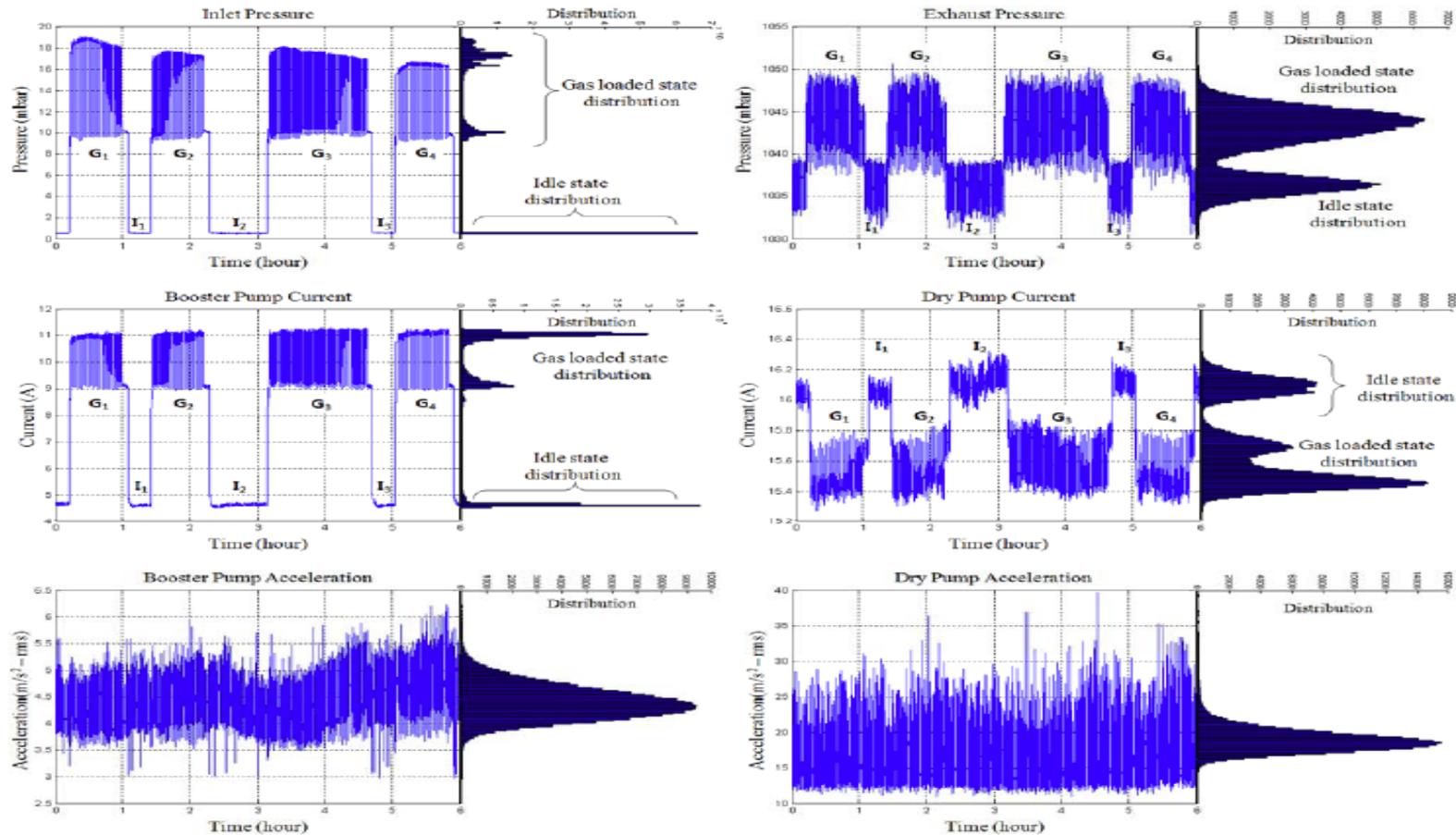
- 한국표준과학연구원, 역학 센터 책임연구원 (1984~현재)
- UST 측정 과학 교수
- 영국 University of Southampton (ISVR) 박사 [1993]
  - Neural Network 기반의 비선형 시스템 제어
- 제 23대 한국음향학회 회장 (2017)
- 학술활동: 한국음향학회, 한국소음진동공학회, 대한기계학회, 한국진공학회, 등
- 관심분야: AI 모델 기반의 신호처리 (반도체 공정 진공펌프 상태 진단 및 예지 보수), 수중 음향 다채널 소나 (고 해상도 영상, InSAS), 차세대 IMU & 실시간 Kalman 필터 구현 등

# 국내 반도체 산업 지원 국책과제 (2008 ~ 2013): “Smart 진공 배기 시스템 개발”



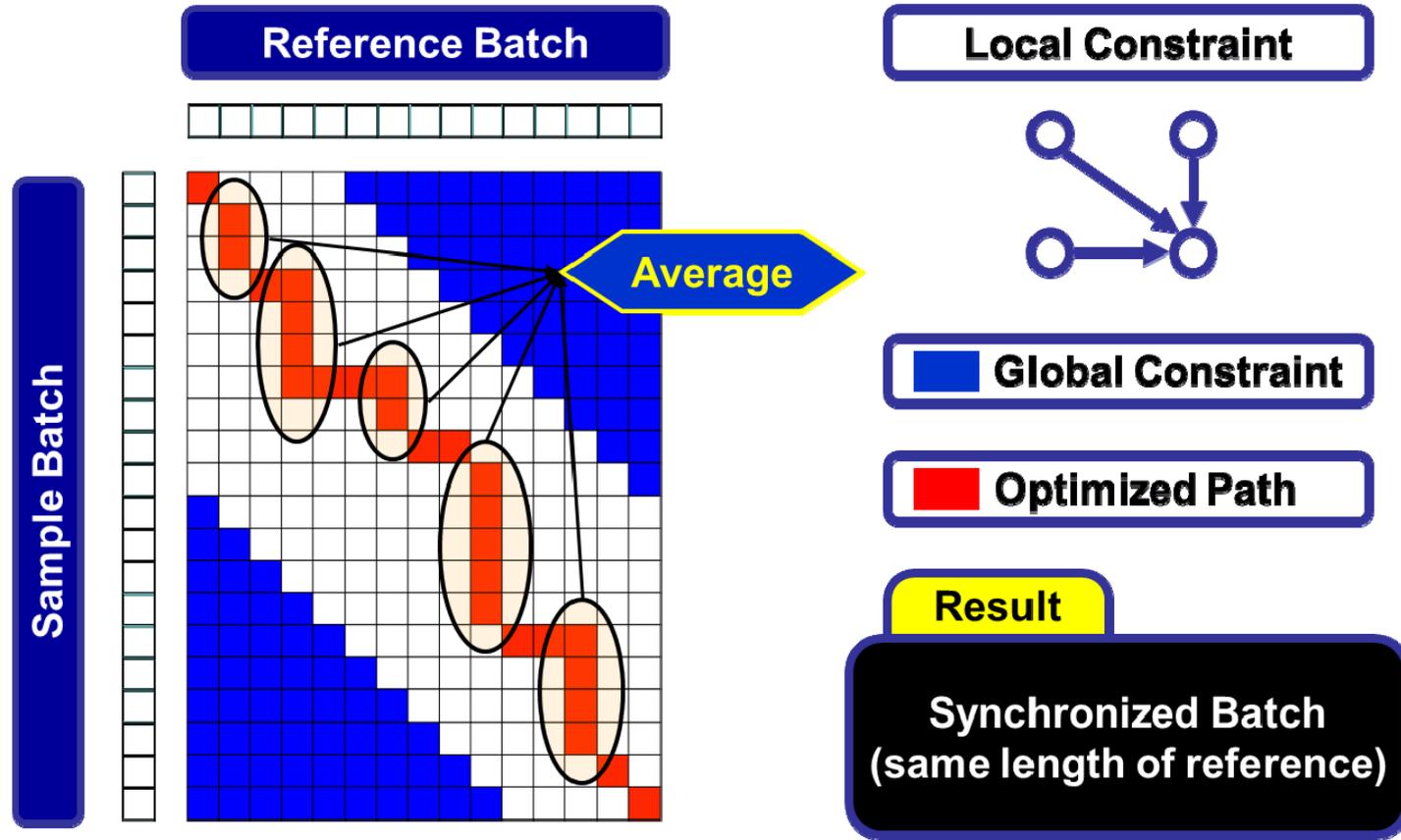
- 2 PCT Patents: Registered in Korea, USA, Japan, China, EU
  - Precision diagnostics and predictive maintenance (PM)

# 반도체 공정용 진공펌프 상태변수들의 분포 특성



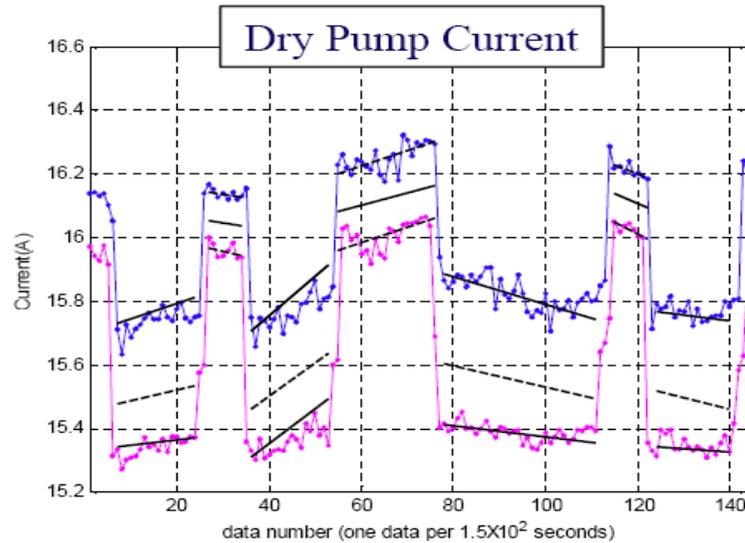
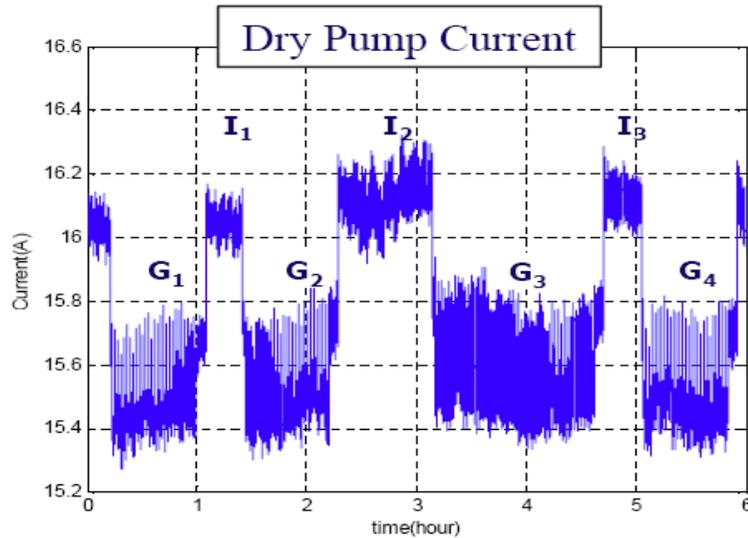
➤ Technical challenges, neither simple pictures nor simple statistical models.

# 공정별 변수 길이 조정: Dynamic Time Wrapping



➤ DTW Scheme: Huge computation load, proper for GPU but not DSP.

# 적응형 인자 모델 (Adaptive Parametric Model, APM)



$$y_{k,n} = a_k \cdot n + b_k$$

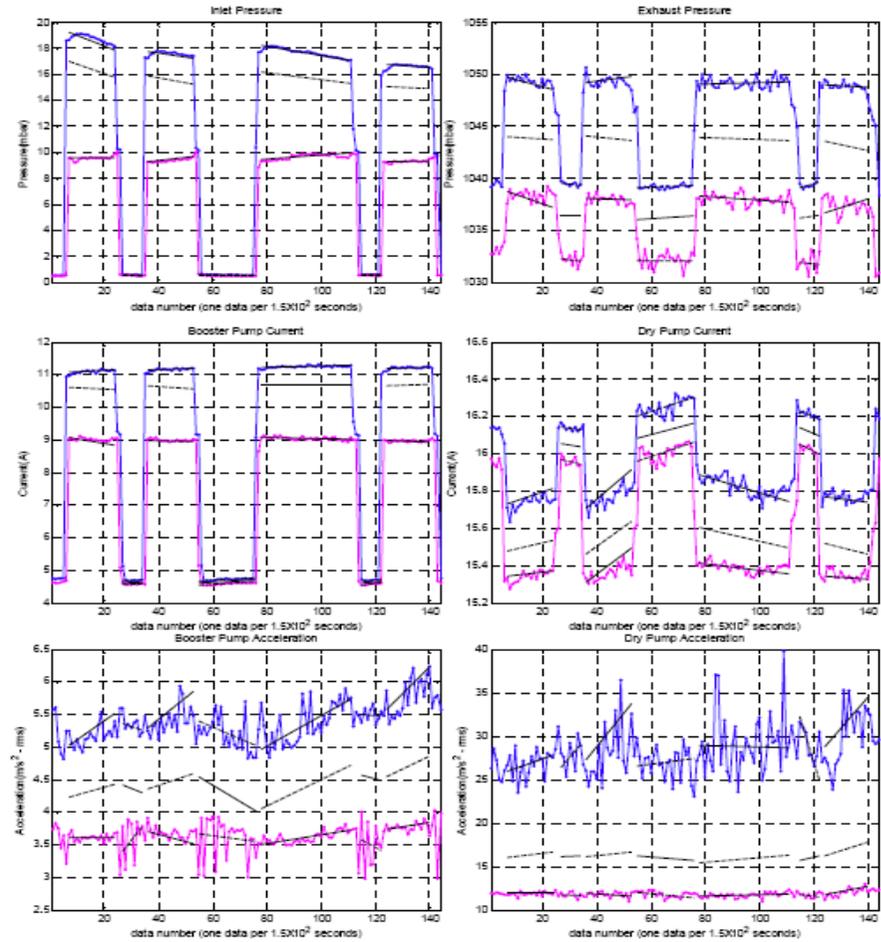
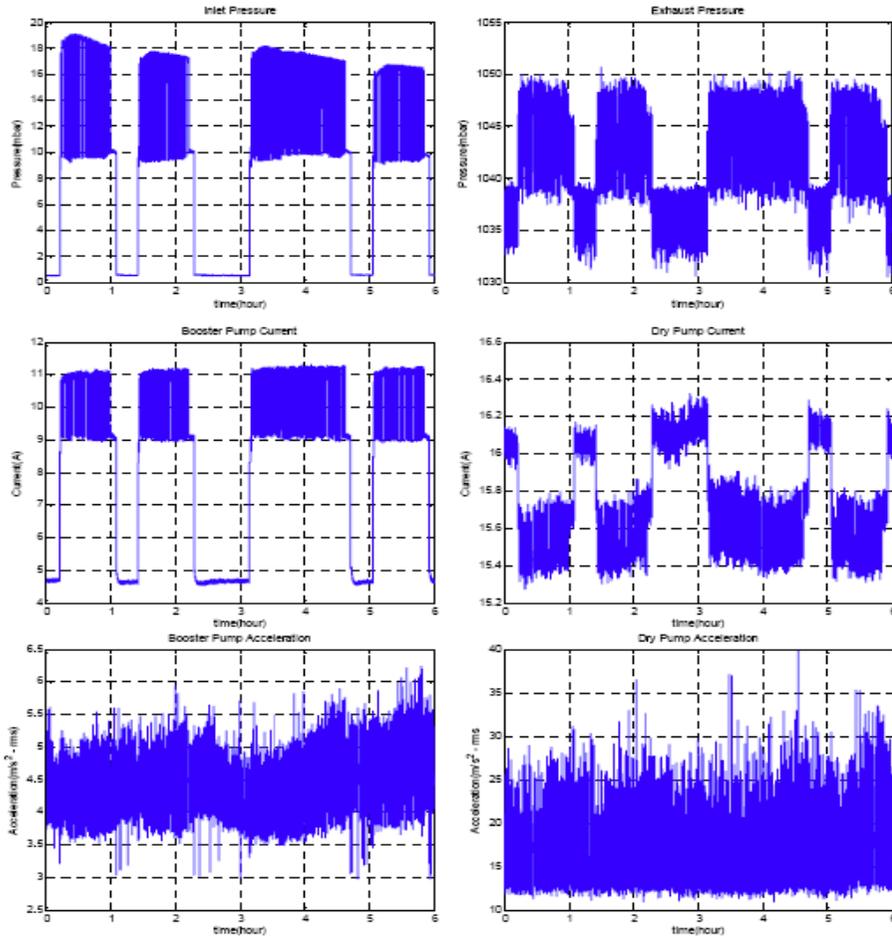
$$a_k = \frac{N \cdot \sum_{n=1}^N n \cdot y_{k,n} - \sum_{n=1}^N n \cdot \sum_{n=1}^N y_{k,n}}{N \cdot \sum_{n=1}^N n^2 - \left(\sum_{n=1}^N n\right)^2}$$

$$b_k = \frac{\sum_{n=1}^N n^2 \cdot \sum_{n=1}^N y_{k,n} - \sum_{n=1}^N n \cdot \sum_{n=1}^N n \cdot y_{k,n}}{N \cdot \sum_{n=1}^N n^2 - \left(\sum_{n=1}^N n\right)^2}$$

$$\sigma_k = \sqrt{\frac{1}{N} \sum_{n=1}^N (y_{k,n} - a_k \cdot n - b_k)^2}$$

➤ APM Capability is tracking the mean trend ( $a \cdot n + b$ ) and the standard deviation  $\sigma$  of each separable distribution of state variables

# 적응형 인자 모델 (APM)과 재구성된 상태변수



➤ What about graphical trend analysis?

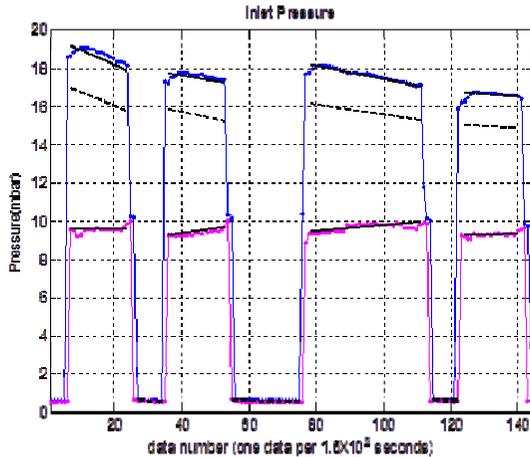
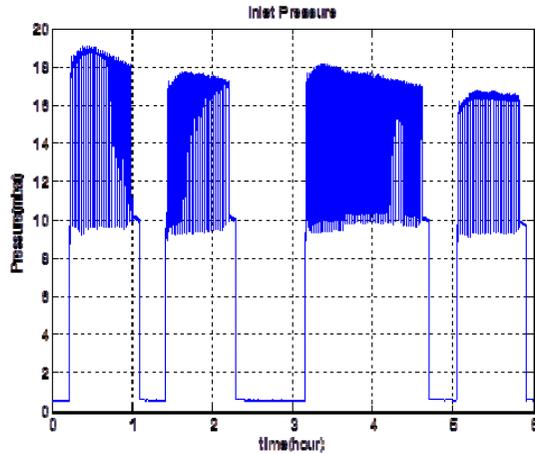
# 추정된 적응형 인자 모델 (APM) 값의 테이블

- ❑ Exhaust pressure difference values  
 : 7.1 mbar (Initial)  
   7.6 mbar (Last)
- ❑ Mean value of supply current (BP)  
 Load : 8.2 A (Initial)  
       8.9 A (Last)  
 Idle : 4.3 A (Initial)  
       3.9 A (Last)
- ❑ Mean value of supply current (DP)  
 Load : 15.8 A (Initial)  
       15.8 A (Last)  
 Idle : 16.2 A (Initial)  
       16.5 A (Last)
- ❑ Vibration Level  
 Mean : 24 % Increment  
 Peak : 5.8% Increment
- ❑ Acoustic Noise Level  
 Mean : 26 % Increment  
 Peak : 99% Increment

Pump Operation Conditions		Step 1	Step 2	Pump Operation Conditions		Step 1	Step 2		
		Gas-Loaded State 1	Idle State1			Gas-Loaded State 1	Idle State1		
Inlet Pressure [mbar]	Mean Value	20.3	0.75	Exhaust Pressure [mbar]	Mean Value	1014.9	1007.3		
	Upper Bound	a <sub>U</sub>	0.084		-0.003	Upper Bound	a <sub>U</sub>	-0.024	0.009
		b <sub>U</sub>	19.3		0.77		b <sub>U</sub>	1018.1	1009.8
		Peak	21.4		1.06		Peak	1018.5	1010.8
	Lower Bound	a <sub>U</sub>	0.086		-0.002	Lower Bound	a <sub>U</sub>	-0.001	0.021
		b <sub>U</sub>	19.1		0.73		b <sub>U</sub>	1012.0	1003.7
BP Supply Current [A]	Mean Value	8.93	3.86	DP Supply Current [A]	Mean Value	15.8	16.5		
	Upper Bound	a <sub>U</sub>	0.015		-0.003	Upper Bound	a <sub>U</sub>	-0.002	0.002
		b <sub>U</sub>	8.79		3.98		b <sub>U</sub>	16.0	16.6
		Peak	9.19		4.10		Peak	16.0	16.7
	Lower Bound	a <sub>U</sub>	0.015		-0.003	Lower Bound	a <sub>U</sub>	0.0000	0.0004
		b <sub>U</sub>	8.67		3.91		b <sub>U</sub>	15.7	16.4
Vibration Level on DP [m/s <sup>2</sup> ]	Mean Value	13.9	13.8	Acoustic Noise Level [Pa]	Mean Value	1.07	1.02		
	Upper Bound	a <sub>U</sub>	-0.033		0.0056	Upper Bound	a <sub>U</sub>	-0.011	-0.003
		b <sub>U</sub>	16.3		15.5		b <sub>U</sub>	1.99	1.75
		Peak	16.7		16.3		Peak	2.29	2.63
	Lower Bound	a <sub>U</sub>	-0.002		12.2	Lower Bound	a <sub>U</sub>	-0.001	0.0004
		b <sub>U</sub>	-0.002		12.3		b <sub>U</sub>	0.75	0.73

➤ What about quantitative trend analysis?

# 적응형 인자 모델 (APM)의 특징



pump operation (time)			process 1 (3150s)	process 2 (3150s)	process 3 (5850s)	process 4 (3300s)
variable	region	symbol				
Inlet Pressure [mbar]	upper bound.	au	-0.08003	-0.03128	-0.03571	-0.0161
		bu	19.217	17.773	18.226	16.766
		σu	0.039051	0.034187	0.048675	0.02256
	lower bound.	al	0.001968	0.024049	0.015727	0.001189
		bl	9.5477	9.2433	9.4297	9.29
		σl	0.019503	0.033994	0.1374	0.03503
Mean	μm	-7.20E-02	-4.04E-02	-2.53E-02	-1.09E-02	
	bm	16.987	15.905	16.156	15.081	
	σm	0.30622	0.32314	0.52289	0.4862	

공정주기 ≈ 1<sup>h</sup>

4개월 누적 DATA(5case)		
분류	10Hz RMS DATA	APM 시계열 DATA
용량	약 5.9 GB	약 0.35 GB
매체	CD 9장	CD 1장

데이터 압축율 ≈ 75

➤ 주기 8시간 LDO 공정에서 1,000 배 이상 데이터 압축을 구현

# 적응형 인자 모델 데이터 구조체 만들기

- Batch Data structure: “Standard database” model
  - Gas Loaded States & Idle States: Old Model of Data Structure

$$X_{IP, GL} = \begin{bmatrix} a_{u1} & b_{u1} & \sigma_{u1} & a_{l1} & b_{l1} & \sigma_{l1} \\ a_{u2} & b_{u2} & \sigma_{u2} & a_{l2} & b_{l2} & \sigma_{l2} \\ a_{u3} & b_{u3} & \sigma_{u3} & a_{l3} & b_{l3} & \sigma_{l3} \\ \vdots & \vdots & \vdots & \vdots & \vdots & \vdots \\ a_{uj} & b_{uj} & \sigma_{uj} & a_{lj} & b_{lj} & \sigma_{lj} \end{bmatrix} \xrightarrow{\text{Batch Number}} \begin{bmatrix} a_1 & b_1 & \sigma_1 \\ a_2 & b_2 & \sigma_2 \\ \vdots & \vdots & \vdots \\ a_j & b_j & \sigma_j \end{bmatrix}$$

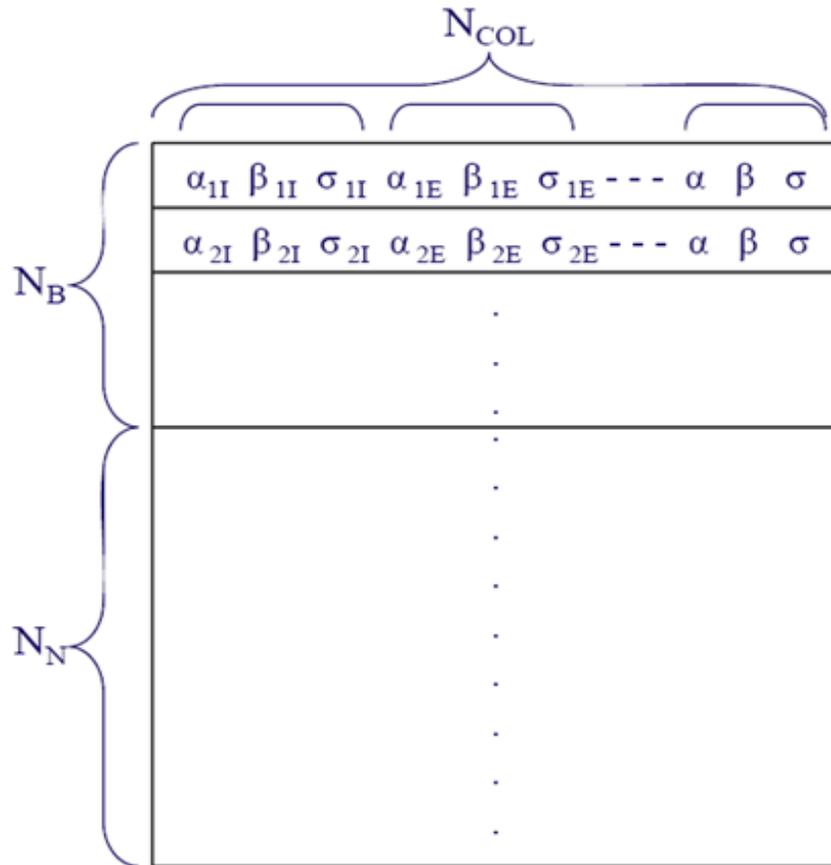
- 전체 상태변수에 대한 Batch Data of j Processes (2D Data Structure)

$$\mathbf{X}_{GL} = \begin{bmatrix} X_{IP, GL} & X_{EP, GL} & X_{BC, GL} & X_{DC, GL} & X_{BA, GL} & X_{DA, GL} & \dots \end{bmatrix}^T$$

$$\mathbf{X}_{ID} = \begin{bmatrix} X_{IP, ID} & X_{EP, ID} & X_{BC, ID} & X_{DC, ID} & X_{BA, ID} & X_{DA, ID} & \dots \end{bmatrix}^T$$

Each **column** corresponding to one process batch data &  
 a number of **columns** corresponding to the number of process batches.

# 적응형 인자 모델 데이터 구조체



- $N_{col}$ : 단위 공정별 APM 인자 수
- $N_B$ : NOC (Normal Operation Condition) 공정 수
- $N_N$ : 상태 진단을 수행 공정 수

➤ Separated "Idle" & "Gas-Loaded" APM Databases

# 정상상태의 기준 배치 데이터: 고유 특징 추출

## ■ 정상운전상태 (Normal Operating Conditions, NOC) Batch Data

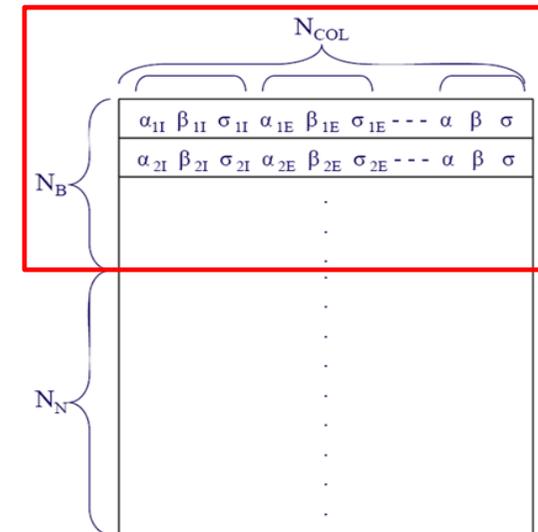
- NOC Batch Data: Collected in the Gas-Loaded & Idle States (GLS & IDS) of the First 7 ~ 35 Process Days (Normally,  $N_{NOC} = 100 \sim 500$  Process Batches)

$$\mathbf{X}_{NOC, GL} \quad \& \quad \mathbf{X}_{NOC, ID}$$

- Singular Value Decomposition (SVD) of NOC Batches:

$$\mathbf{X}_{NOC} = \mathbf{U}\mathbf{\Lambda}\mathbf{V}^T = \mathbf{U}_S\mathbf{\Lambda}_S\mathbf{V}_S^T + \mathbf{E} \leftarrow \mathbf{E} = \sum_{i=N_S+1}^{N_{NOC}} \Lambda_i \mathbf{u}_i \mathbf{v}_i^T$$

- $\mathbf{U}_S$ : **Column**-orthogonal matrix selected from  $N_S$  significant SVs
- $\mathbf{\Lambda}_S$ : Diagonal matrix ( $N_S$  significant SVs)
- $\mathbf{V}_S$ : **Column**-orthogonal matrix selected from  $N_S$  SVs
- $\mathbf{E}$ : Residual (noise space) components of NOC batch data



# 현 공정 데이터와 정상 공정 데이터 (NOC) 비교

## ■ Comparison between k-th Process Batch & NOC Batches:

- Projecting the k-th process batch data  $\mathbf{x}_k$  to the NOC batch:

$$\mathbf{t}_k = \mathbf{x}_k^T \mathbf{U}_S$$

- Calculating the Hotelling's  $T^2$  (Similarity): **"1<sup>st</sup> Statistic"**

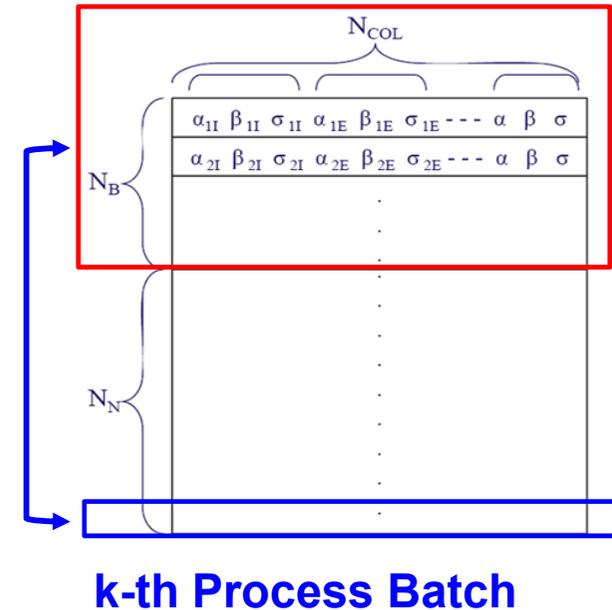
$$T_k^2 = \mathbf{t}_k \mathbf{S}^{-1} \mathbf{t}_k^T \quad \mathbf{S} = \frac{1}{N_{NOC} - 1} \text{diag} \left[ \Lambda_1^2 \quad \Lambda_2^2 \quad \bullet \quad \bullet \quad \bullet \quad \Lambda_{N_S}^2 \right]$$

- Calculating the k-th batch residual:

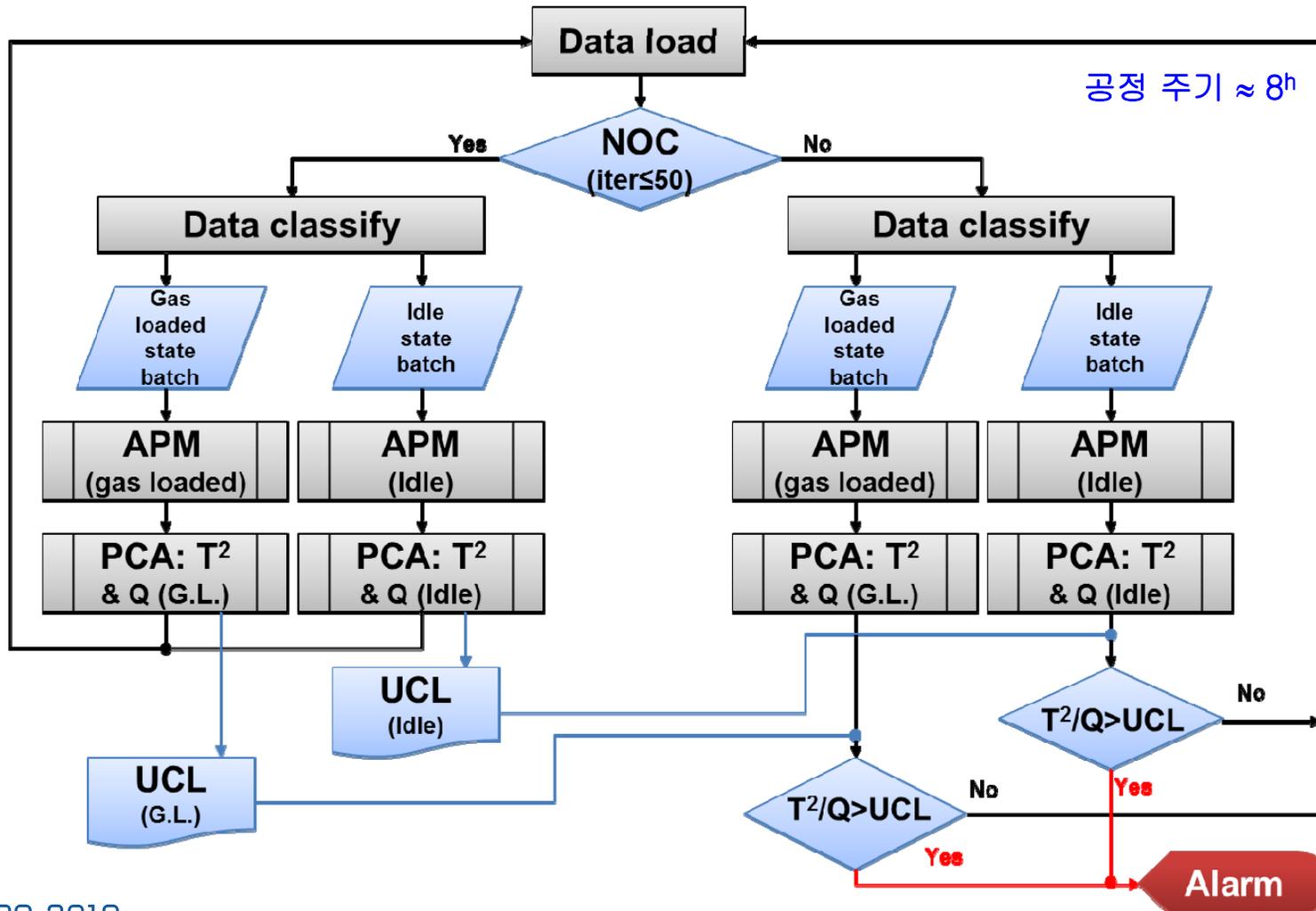
$$\mathbf{e}_k = \mathbf{x}_k - \mathbf{U}_S \mathbf{t}_k$$

- Calculating Sum of Squared Residuals Q (Difference): **"2<sup>nd</sup> Statistic"**

$$Q_k = \mathbf{e}_k^T \mathbf{e}_k$$



# T<sup>2</sup>와 Q 기반의 자기진단 흐름도: LTO 공정 예



# MathWorks 솔루션을 프로젝트에 적용한 이유

- MATLAB은 행렬기반의 언어로 직관적으로 쉬운 데이터 분석 및 수학적 모델링 구현

```

< M A T L A B >
Version of 25 May 1982
Ported to Win32 on 26 Oct 2000

HELP is available
<>A = [1 -1 0; -1 2 -1; 0 -1 1]
A
=
    1.0000   -1.0000    0.0000
   -1.0000    2.0000   -1.0000
    0.0000   -1.0000    1.0000

<>[U S V] = svd(A)
U
=
    0.4082   -0.7071    0.5774
   -0.8165    0.0000    0.5774
    0.4082    0.7071    0.5774

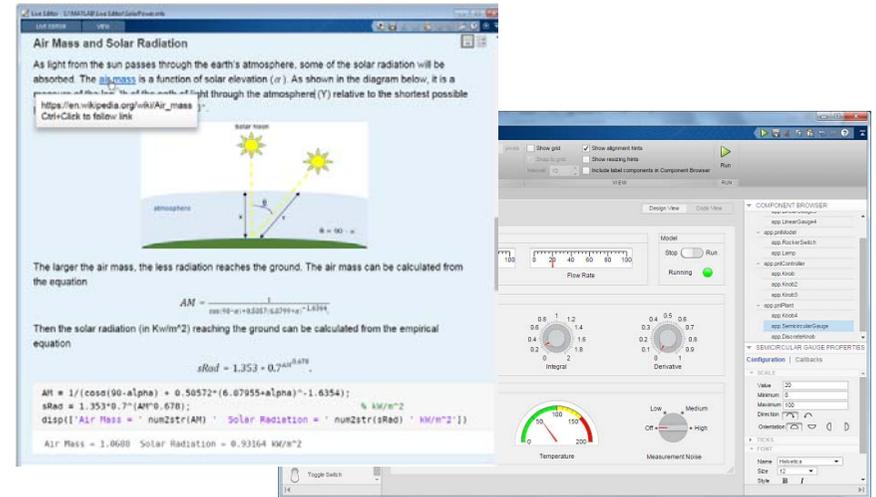
S
=
    3.0000    0.0000    0.0000
    0.0000    1.0000    0.0000
    0.0000    0.0000    0.0000

V
=
    0.4082   -0.7071    0.5774
   -0.8165    0.0000    0.5774
    0.4082    0.7071    0.5774
    
```



- MATLAB은 수치 해석 분야의 산 역사이며 선형 대수학의 표준 함수들(libraries)을 제공.

- 엔지니어와 과학자에게 최적화된 연산 도구들 제공.



# Matlab 기반의 자기 진단 구현

## ■ Why Matlab Codes for Self-Diagnosis of Vacuum Pumps?

- Best choice for linear algebra, such as matrix works (shown so far)
- Personal attitude of coding ideas: Long history of using matlab in my life

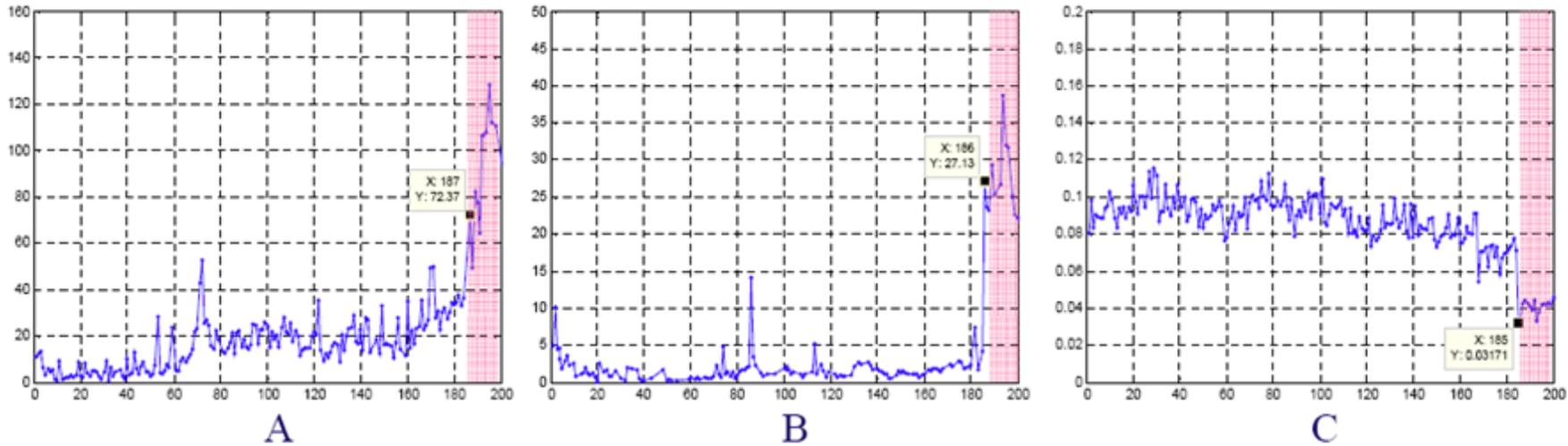
## ■ 7 Stepped Computation Sequences:

- Step 1: Reading log files and check 'abnormal and/or crashed' data
- Step 2: Classifying the idle and gas-loading states using pump motor current signals
- Step 3: Testing multi-distribution gas-loaded states and separating them
- Step 4: Estimating APM parameters of NOC batches and stacking them (NOC batch database)
- Step 5: Extracting distinctive feature vectors from NOC batch matrices using SVD
- Step 6: Estimating idle and gas-loaded APM parameters for each process
- Step 7: Projecting the current APM batch vectors to the NOC feature vectors, evaluating and plotting T2 and Q charts.

## ■ Matlab Code Structure :

- Legacy script file: "VP\_Diagnosis.m"
- Live script file: "VP\_Diagnosis\_live.mlx" → Illustrating its pdf-format file
- Matlab functions called: svd, mldivide (\), chi2pdf, fpdf, and graphics etc.

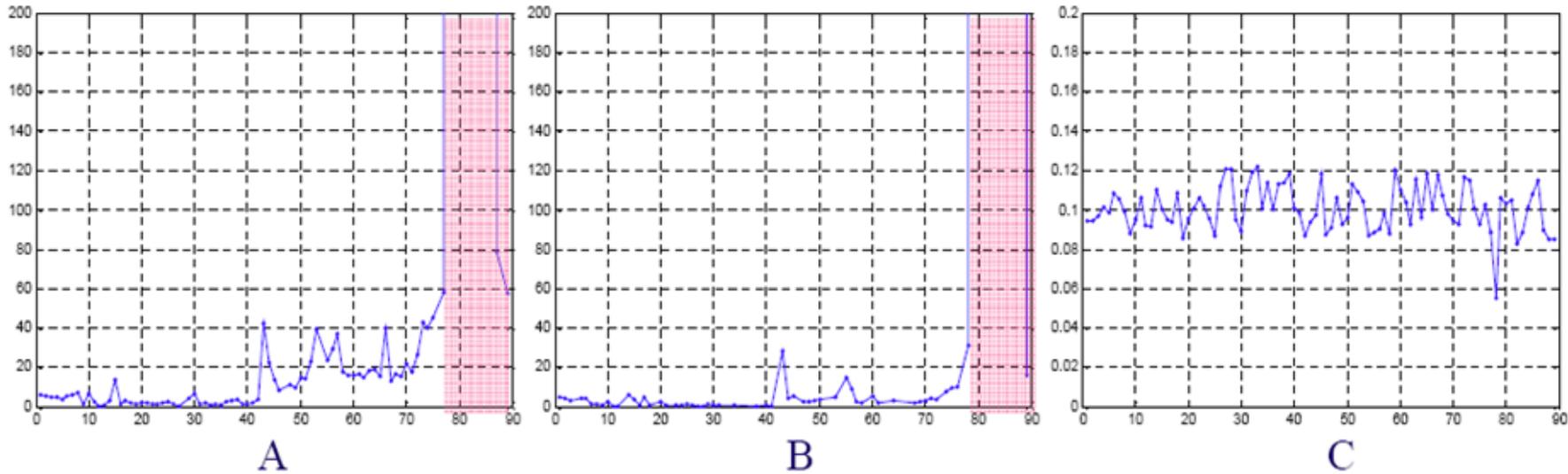
# 진단 사례 1: 진공펌프 배기성능 (Pumping Speed) 저하



	(A) : $T^2$ from Gas loaded state batch	(B) : $T^2$ from Idle state batch	(C) : PSI
Batch NO.	187 <sup>th</sup>	186 <sup>th</sup>	185 <sup>th</sup>

- All diagnostic Model detect the trouble occurrence
- PSI predicts that the pump system will shut down

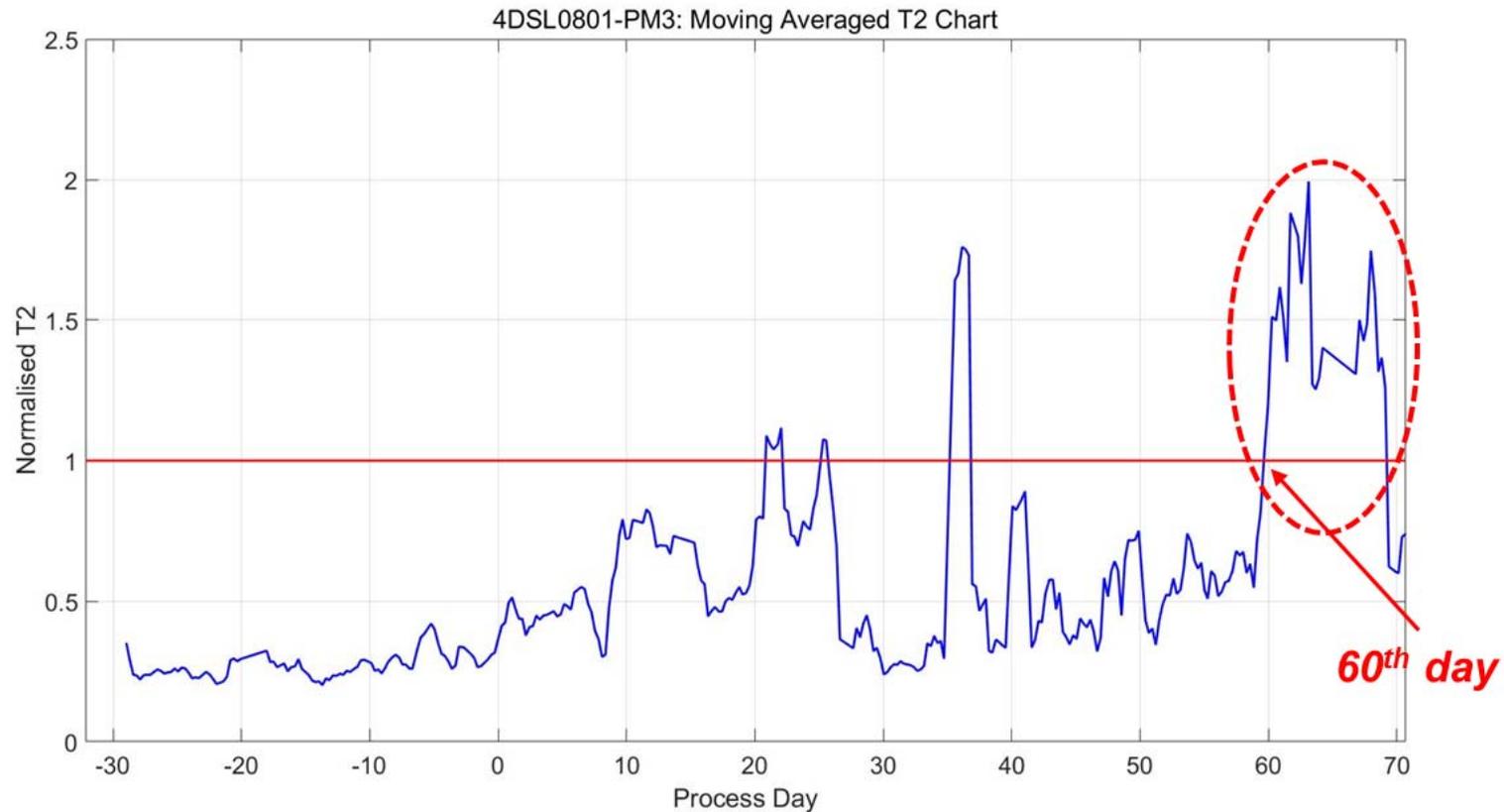
# 진단 사례 2: BP 모터 과부하 (Overload)



	(A) : T <sup>2</sup> from Gas loaded state batch	(B) : T <sup>2</sup> from Idle state batch	(C) : PSI
Batch NO.	77 <sup>th</sup>	78	X

- T<sup>2</sup> detect the trouble occurrence
- PSI can't catch the trouble occurrence

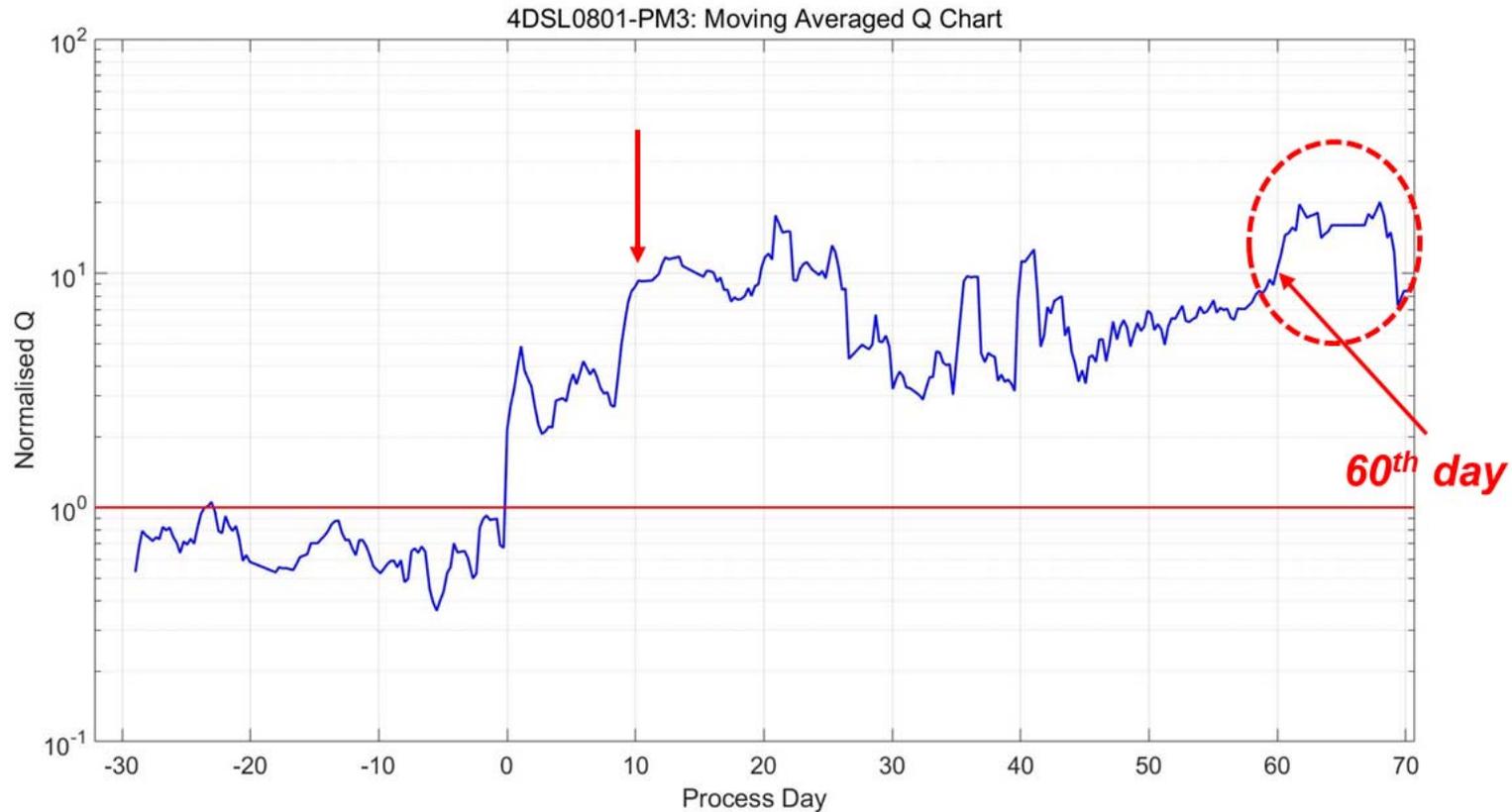
# 진단 사례 3:



## ■ Features of 5-Process Moving Averaged T2 Chart:

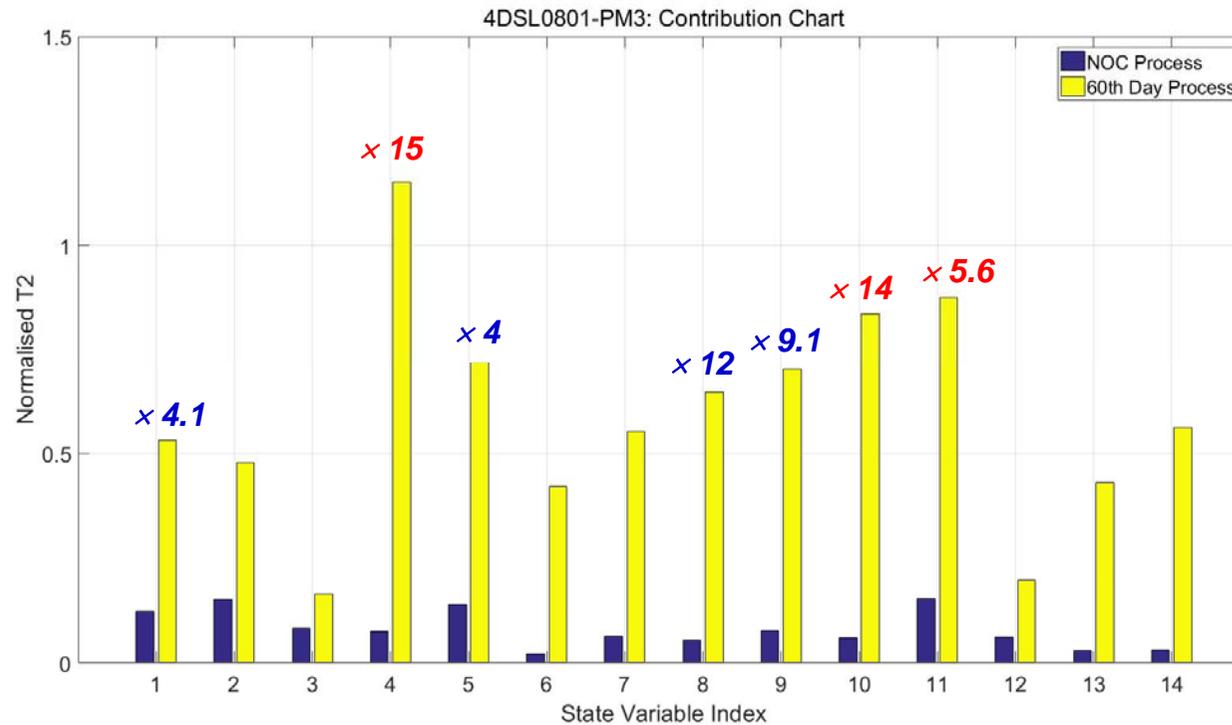
- First 3 peaks: Going back to the normal process states
- 4<sup>th</sup> jumped level > 99% C.L. : Stayed in 9 days after 60<sup>th</sup> day

# 진단 사례 3:



- **Features of 5-Process Moving Averaged Q Chart:**
  - First 4 peaks: Going back to the process states of  $Q \leq 10$
  - 4<sup>th</sup> jumped level  $> 10 \times Q\text{-C.L.}$ : Stayed in 9 days after 60<sup>th</sup> day

# 진단 사례 3:



## ■ T2 Contribution Chart:

- #1: BP Current, #5: BP Power, #8: DP Current, #9: DP Power
- #4: BP Inverter Heater Temp, #11: Invert Heater Temp, #10: DP Stator Temp. : **Significant state variables MUST be considered for diagnosis**

# 결론

- **공정현장 Log 데이터 기반의 상태 진단 기술 유효성 검정: 1단계**
  - LTO공정 60일째부터 9일 동안 이상 정보 확인: **“긍정적 PM 유효성”**
    - 20일경과 후 3회 간헐적 경보: **경보 후 정상으로 복귀**
  - Matlab Toolbox 혹은 App 기반의 코드 표준화 진행 중
  
- **공정 현장 적용 및 향후 계획:**
  - 세계선도 국내 반도체 및 디스플레이 제조사 진공펌프 운용 실태
    - 반도체(S사, H사): 5 ~ 6만 대의 건식 진공펌프
    - 디스플레이(S사, L사): 2 ~ 3 만 대의 건식 진공펌프
  - 200~300 종의 공정 별 수십 ~ 수백 대의 진공펌프 상태변수 DB 구축 및 실시간 진단:
    - Matlab 기반의 데이터 관리: **datastore, timetable, table, tall, etc**
    - 병렬 및 분산 처리 채택: **실시간 구현**
    - Matlab 전문가 그룹과 긴밀한 협조: **AI 및 Machine Learning 등과 융합.**