



2017年結構抗震與健康監測新技術研討會



## 結構健康監測新技術

應用巨量數據縮減技術於結構健康診斷及線上子空間系統識別法  
於結構勁度之即時量化評估



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# Introduction (I)

Structural damage due to earthquake, scouring, aging, environmental impact load, etc.



Bridge collapse without warning



Bridge during scouring



Building damage during earthquake



Cracks of steel structure



Wind turbine blade



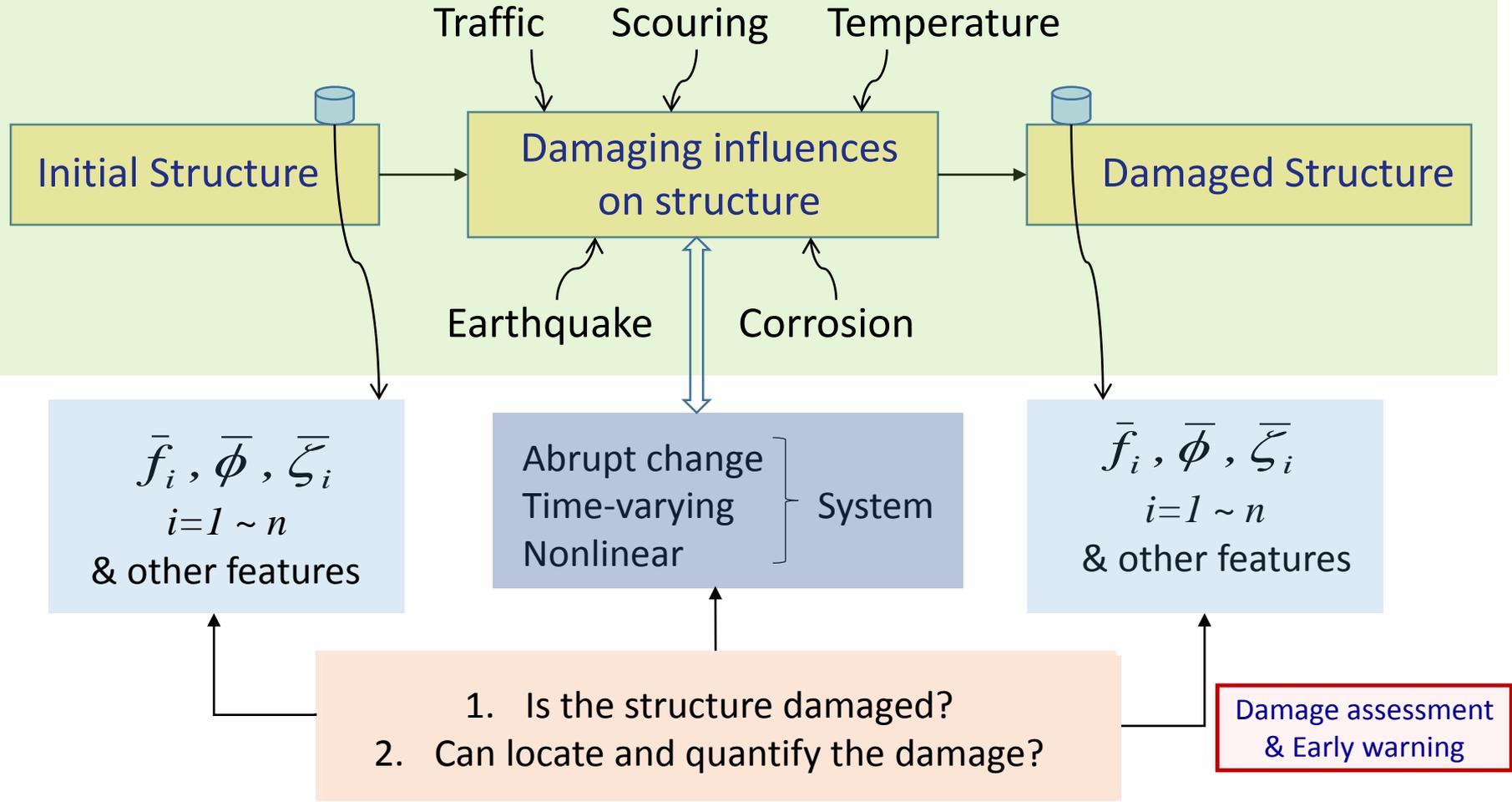
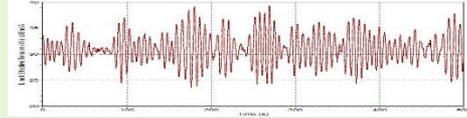
Collapse of building structure



Collapse Bridge due to scouring



## Environmental influences



# Introduction (II)

Damage assessment of structure using **feature extraction** and **system identification** techniques is needed to explore the current state of the structure.

**Features are used to answer the following:**

## 1 Is the system damaged?

- Group classification problem for supervised learning
- Identification of outliers for unsupervised learning

## 2 Where is the damage located?

- Group classification or regression analysis problem for supervised learning
- Identification of outliers for unsupervised learning

## 3 What type of damage is present?

- Can only be answered in a supervised learning mode
- Group classification

## 4 What is the extent of damage?

- Can only be answered in a supervised learning mode
- Group classification or regression analysis

## 5 What is the remaining useful life of the structure? (Prognosis)

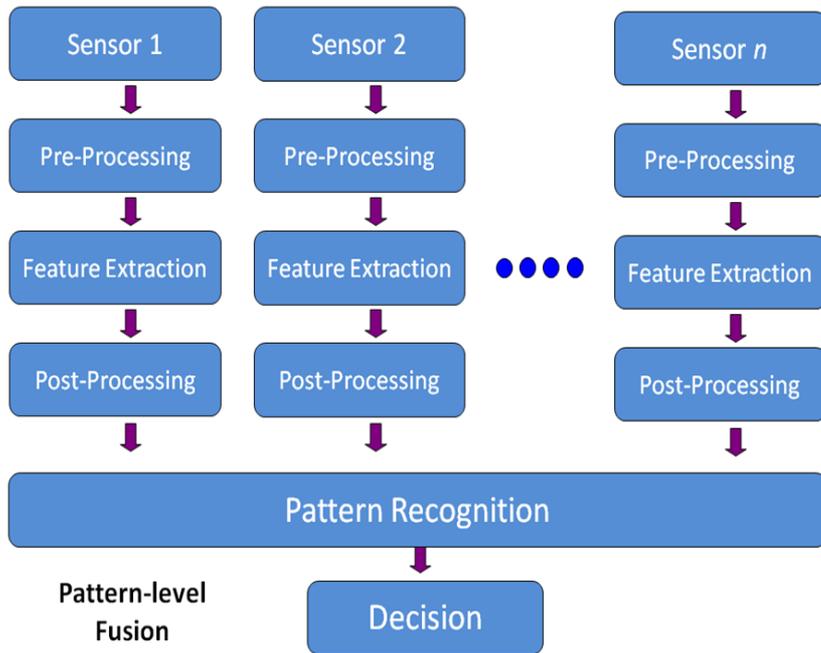
- Can only be answered in a supervised learning mode
- Regression analysis



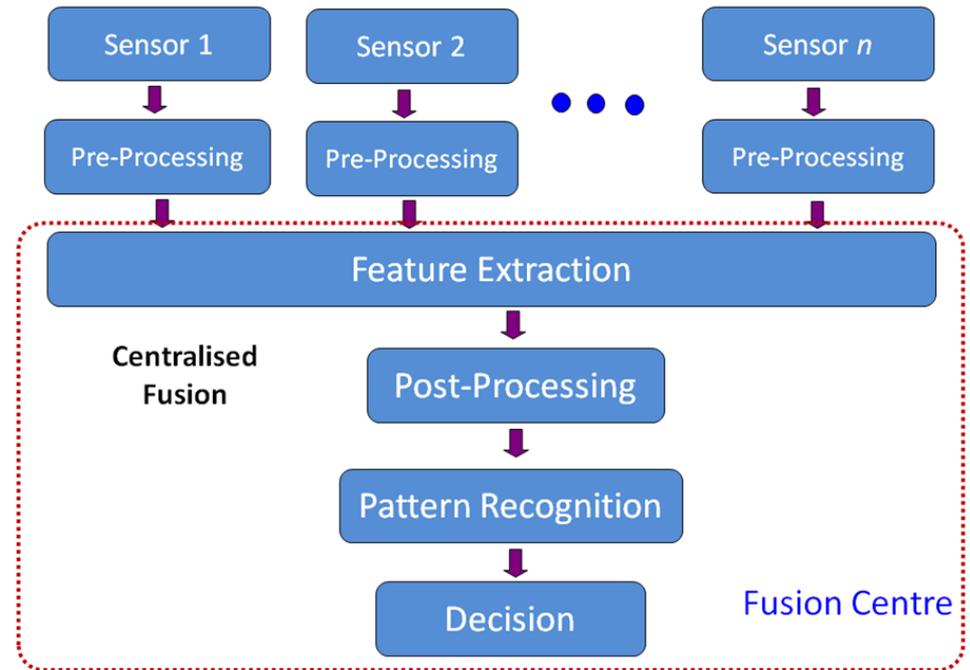
# Research Objective

**Objective:** Develop an **on-line and almost real-time monitoring** of structural modal parameters (or feature extraction techniques) under operating conditions/earthquake loading, and conduct damage assessment on the structure.

## Pattern-level Data Fusion



## Centralized Data Fusion



*Vibration-based damage detection: a multi-sensor architecture*



## ◆ 結構系統識別方法：

### ● 結構常態振動量測(微振)

√ 全自動隨機子空間識別法 (Covariance-driven stochastic subspace ID, SSI-COV)

√ 多重輸出AR Model (MV-AR)

### ● 結構地震反應量測

√ 子空間識別法 (Subspace Identification, SI)

√ 遞迴性子空間系統識別 (Recursive Subspace Identification, RSI)

## ◆ 結構健康診斷損傷評估

### ● 結構常態振動量測(微振)

√ 零子空間損傷識別 (Null-space damage index, Q-test)

√ 2D可視化技術結構損傷評估 (Sammon map)

√ 相關性指標 (Wavelet-based correlation of scalogram)

√ 多重奇異值譜分析法 (Multivariate Singular Spectrum Analysis, MSSA)

### ● 結構地震反應量測(結合結構系統識別)

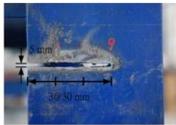
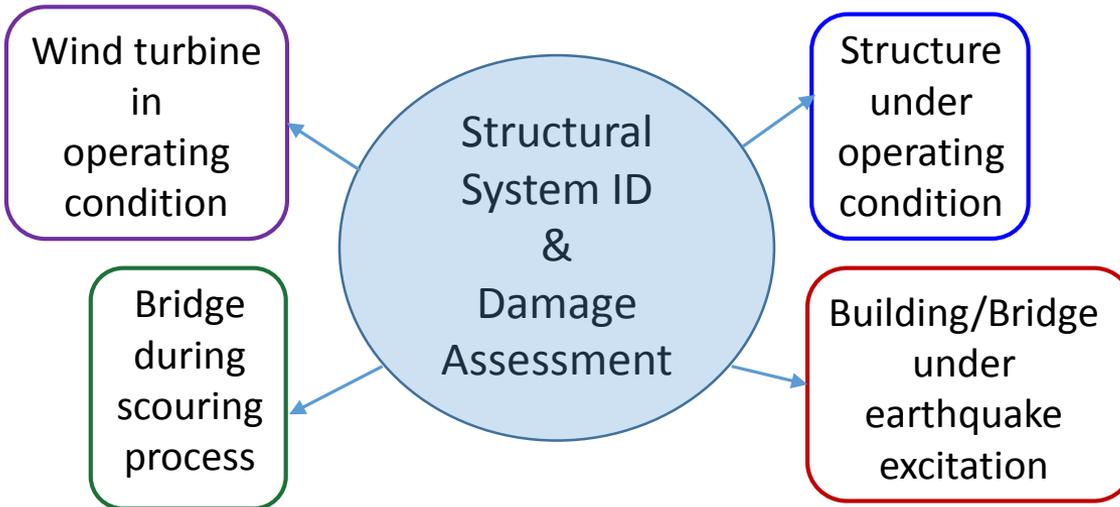
√ 勁度折減評估 (LSSM+EMCM)

Level-1  
&  
Level-2

Level-3  
&  
Level-4



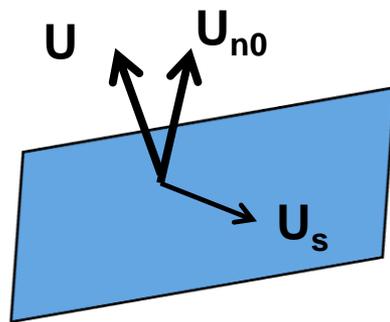
# Structural Health Monitoring: Experimental Studies



(Level-1 Damage Assessment) Null-space and subspace damage index:  $DI_n$  &  $DI_s$

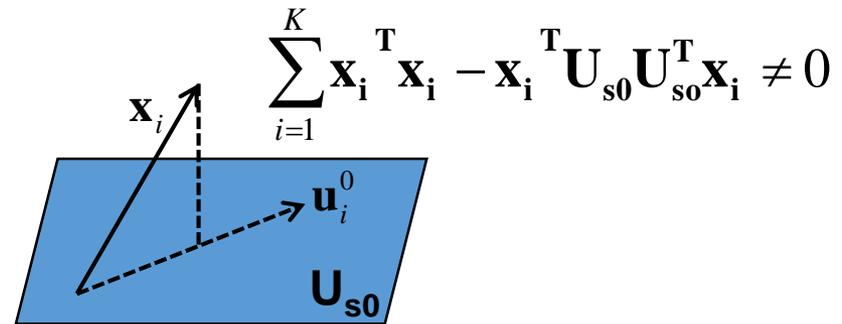
$$\mathbf{Y} = \begin{bmatrix} y[1] & y[2] & \cdots & y[K] \\ y[2] & y[3] & \cdots & y[K+1] \\ \vdots & \vdots & \ddots & \vdots \\ y[L] & y[L+1] & \cdots & y[N] \end{bmatrix} = \begin{bmatrix} \mathbf{Y}_p \\ \mathbf{Y}_f \end{bmatrix} \longrightarrow \mathbf{T} = \mathbf{Y}_f \mathbf{Y}_p^T \longrightarrow \mathbf{X} = \mathbf{T}$$

$$\mathbf{X}_0 = [\mathbf{U}_{s0} \quad \mathbf{U}_{n0}] \begin{bmatrix} \mathbf{S}_{s0} & \mathbf{0} \\ \mathbf{0} & \mathbf{S}_{n0} \end{bmatrix} [\mathbf{V}_{s0} \quad \mathbf{V}_{n0}]^T \approx \mathbf{U}_{s0} \mathbf{S}_{s0} \mathbf{V}_{s0}^*$$



$$\mathbf{U}_{n0}^T \mathbf{U}_s \neq 0$$

$$DI_n = \text{mean}\{|\mathbf{U}_{n0}^T \mathbf{U}_s|\}$$



$$\sum_{i=1}^K \mathbf{x}_i^T \mathbf{x}_i - \mathbf{x}_i^T \mathbf{U}_{s0} \mathbf{U}_{s0}^T \mathbf{x}_i \neq 0$$

$$DI_s = \frac{\sum_{i=1}^K \mathbf{x}_i^T \mathbf{x}_i - \mathbf{x}_i^T \mathbf{U}_{s0} \mathbf{U}_{s0}^T \mathbf{x}_i}{\sum_{i=1}^K \mathbf{x}_i^T \mathbf{x}_i}$$



## Stage I: Decomposition

### Step 1: Embedding.

1. Develop the trajectory matrix:  
(from each record)

$$\mathbf{X}_l = \begin{bmatrix} x_l(1) & x_l(2) & \cdots & x_l(M) \\ x_l(2) & x_l(3) & \cdots & x_l(M+1) \\ \vdots & \vdots & \vdots & \vdots \\ x_l(N') & x_l(N'+1) & \cdots & x_l(N) \end{bmatrix}$$

2. Develop block Hankel trajectory matrix:  
(combine all records)

$$\mathbf{X}_V = \begin{bmatrix} \mathbf{X}_1 \\ \vdots \\ \mathbf{X}_D \end{bmatrix}$$

### Step 2: Singular Value Decomposition

3. Perform SVD of  $\mathbf{X}_V$ :

$$\mathbf{X}_V = \mathbf{X}_{V1} + \mathbf{X}_{V2} + \cdots + \mathbf{X}_{VLsum}$$

where  $\mathbf{X}_{Vi} = \sqrt{\lambda_{Vi}} \mathbf{U}_{Vi} \mathbf{V}_{Vi}^T$        $\mathbf{V}_{Vi} = \mathbf{X}_V^T \mathbf{U}_{Vi} / \sqrt{\lambda_{Vi}}$

$\lambda_{V_1}, \dots, \lambda_{V_{Lsum}}$  and  $\mathbf{U}_{V_1}, \dots, \mathbf{U}_{V_{Lsum}}$

are the eigenvalue and eigenvector of  $\mathbf{X}_V \mathbf{X}_V^T$



# Damage Detection Algorithms: Centralized fusion (MSSA)

## Stage II: Reconstruction

Block Hankel trajectory matrix  $\mathbf{X}_V = \begin{bmatrix} \mathbf{X}_1 \\ \vdots \\ \mathbf{X}_D \end{bmatrix}$

$$\tilde{\mathbf{C}} = \mathbf{X}_V \mathbf{X}_V^T = \begin{pmatrix} \mathbf{X}_1 \mathbf{X}_1^T & \mathbf{X}_1 \mathbf{X}_2^T & \cdots & \mathbf{X}_1 \mathbf{X}_D^T \\ \mathbf{X}_2 \mathbf{X}_1^T & \mathbf{X}_2 \mathbf{X}_2^T & \cdots & \mathbf{X}_2 \mathbf{X}_D^T \\ \vdots & \vdots & \mathbf{X}_d \mathbf{X}_{d'}^T & \vdots \\ \mathbf{X}_D \mathbf{X}_1^T & \mathbf{X}_D \mathbf{X}_2^T & \cdots & \mathbf{X}_D \mathbf{X}_D^T \end{pmatrix}$$

Eigenelements: Determine **eigenvalues** and **eigenvectors** of  $\tilde{\mathbf{C}}$

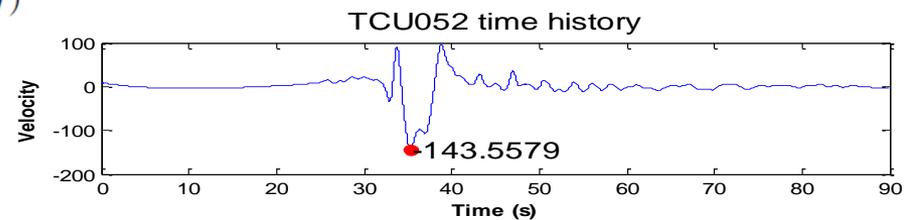
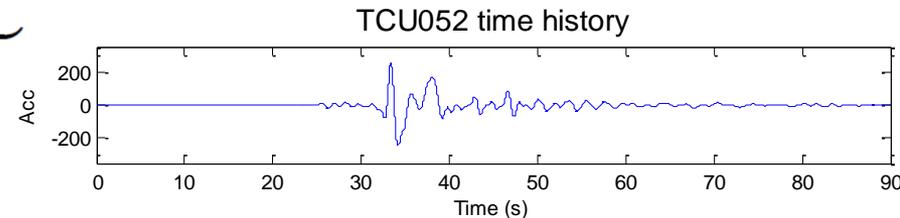
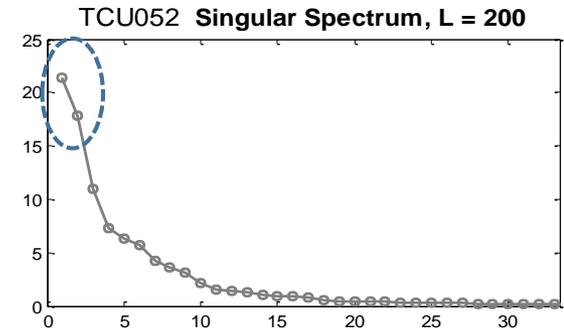
$$\tilde{\mathbf{C}} \tilde{\mathbf{e}}_k = \lambda_k \tilde{\mathbf{e}}_k, \quad k = 1 \dots DM$$

Principal components: Project  $X(t)$  onto  $\tilde{\mathbf{e}}_k$

$$A_k(t) = \underbrace{\sum_{d=1}^D \sum_{j=1}^M x_d(t+j-1) e_k^d(j)}_{\text{SSA}}$$

Reconstructed components: Combine PCs with  $\tilde{\mathbf{e}}_k$

$$r_k^d(t) = \frac{1}{M} \sum_{j=1}^M A_k(t-j+1) e_k^d(j)$$



# System Identification: SSI-COV (for ambient data)

Gather the output data in data sequence vector:

$$\mathbf{y}_k^+ \equiv \begin{bmatrix} \mathbf{y}_{k-i+1} \\ \mathbf{y}_{k-i+2} \\ \dots \\ \mathbf{y}_k \end{bmatrix}, \mathbf{y}_k^{-T} \equiv \begin{bmatrix} \mathbf{y}_{k-i}^T & \mathbf{y}_{k-i-1}^T & \dots & \mathbf{y}_{k-2i+1}^T \end{bmatrix}$$

$$\mathbf{y}_k^+ \in \mathcal{R}^{il \times 1} \quad \mathbf{y}_k^{-T} \in \mathcal{R}^{1 \times il}$$

$l$  is the number of sensors and  
 $i$  is number of block rows

Form the block Hankel covariance matrix:

$$\mathbf{H}_N^{\text{cov}} = E[\mathbf{y}_k^+ \mathbf{y}_k^{-T}] = \frac{1}{\tilde{P}} \sum_{k=2i}^N \mathbf{y}_k^+ \mathbf{y}_k^{-T}$$

Factorization of the block Hankel covariance matrix through SVD:

$$\mathbf{H}^{\text{cov}} = \begin{bmatrix} \mathbf{R}_1 & \mathbf{R}_2 & \dots & \mathbf{R}_i \\ \mathbf{R}_2 & \mathbf{R}_3 & \dots & \mathbf{R}_{i+1} \\ \dots & \dots & \dots & \dots \\ \mathbf{R}_i & \mathbf{R}_{i+1} & \dots & \mathbf{R}_{2i-1} \end{bmatrix} = \mathbf{O}_i \mathbf{\Omega}_i = \begin{bmatrix} \mathbf{C} \\ \mathbf{CA} \\ \dots \\ \mathbf{CA}^{i-1} \end{bmatrix} \begin{bmatrix} \mathbf{G} & \mathbf{AG} & \dots & \mathbf{A}^{i-1} \mathbf{G} \end{bmatrix}$$

$\mathbf{R}_i = E[\mathbf{y}_k \mathbf{y}_{k-i}^T]$

Obtain the system matrices ( $\mathbf{A}, \mathbf{C}$ ):

$$\mathbf{C} = \mathbf{O}_i(1:l,:)$$

$$\begin{bmatrix} \mathbf{CA} \\ \mathbf{CA}^2 \\ \dots \\ \mathbf{CA}^i \end{bmatrix} = \begin{bmatrix} \mathbf{C} \\ \mathbf{CA} \\ \dots \\ \mathbf{CA}^{i-1} \end{bmatrix} \mathbf{A}$$

$$\mathbf{A} = \mathbf{O}_i(1:l(i-1),:)^{\lambda} \mathbf{O}_i(l+1:li,:)$$

Traditional Singular Value Decomposition:

$$\mathbf{H}^{\text{cov}} = \mathbf{U} \mathbf{S} \mathbf{V}^T = \begin{matrix} \text{System order} \\ \left( \mathbf{U}_1 \quad \mathbf{U}_2 \right) \end{matrix} \begin{pmatrix} \mathbf{S}_1 & 0 \\ 0 & 0 \end{pmatrix} \begin{pmatrix} \mathbf{V}_1^T \\ \mathbf{V}_2^T \end{pmatrix}$$

Find the Observability matrix  $\mathbf{O}_i$  from the column subspace  $\mathbf{U}_1$ :

$$\mathbf{O}_i = \mathbf{U}_1 \mathbf{S}_1^{1/2}$$



# Subspace Identification: Tradition (for EQ excitation)

$$\mathbf{X}_{(k+1)} = \mathbf{A}_d \cdot \mathbf{X}_{(k)} + \mathbf{B}_d \cdot \mathbf{u}_{(k)} + \mathbf{w}_{(k)}$$

$$\mathbf{y}_{(k+1)} = \mathbf{C}_c \cdot \mathbf{X}_{(k)} + \mathbf{D}_c \cdot \mathbf{u}_{(k)} + \mathbf{v}_{(k)}$$



$$\mathbf{Y}_f = \mathbf{\Gamma}_i \cdot \mathbf{X}_f + \mathbf{H}_i \cdot \mathbf{U}_f + \mathbf{G}_i \cdot \mathbf{W}_f + \mathbf{V}_f$$

## Approach 1: Orthogonal Projection:

$$\begin{aligned} \mathbf{U}_f &\rightarrow \mathbf{Y}_{f(k)} \mathbf{\Pi}_{U_{f(k)}}^\perp = \mathbf{\Gamma}_i \mathbf{X}_f \cdot \mathbf{\Pi}_{U_{f(k)}}^\perp + \mathbf{H}_i \mathbf{U}_{f(k)} \cdot \mathbf{\Pi}_{U_{f(k)}}^\perp + \mathbf{G}_i \mathbf{W}_{f(k)} \cdot \mathbf{\Pi}_{U_{f(k)}}^\perp + \mathbf{V}_{f(k)} \cdot \mathbf{\Pi}_{U_{f(k)}}^\perp \\ \mathbf{\Xi}_p^T &\rightarrow \mathbf{Y}_{f(k)} \mathbf{\Pi}_{U_{f(k)}}^\perp \mathbf{\Xi}_{p(k)}^T = \mathbf{\Gamma}_i \mathbf{X}_f \mathbf{\Pi}_{U_{f(k)}}^\perp \cdot \mathbf{\Xi}_{p(k)}^T + \mathbf{G}_i \mathbf{W}_{f(k)} \mathbf{\Pi}_{U_{f(k)}}^\perp \cdot \mathbf{\Xi}_{p(k)}^T + \mathbf{V}_{f(k)} \mathbf{\Pi}_{U_{f(k)}}^\perp \cdot \mathbf{\Xi}_{p(k)}^T \\ &\approx \mathbf{\Gamma}_i \mathbf{X}_f \mathbf{\Pi}_{U_{f(k)}}^\perp \mathbf{\Xi}_{p(k)}^T \end{aligned}$$

$$\begin{aligned} \mathbf{O}_{(k)}^{Orthogonal} &= \mathbf{Y}_{f(k)} \mathbf{\Pi}_{U_{f(k)}}^\perp \mathbf{\Xi}_{p(k)}^T \\ &= \mathbf{USV}^T = [\mathbf{U}_1 \quad \mathbf{U}_2] \begin{bmatrix} S_1 & 0 \\ 0 & S_2 \approx 0 \end{bmatrix} \begin{bmatrix} \mathbf{V}_1^T \\ \mathbf{V}_2^T \end{bmatrix} \approx \mathbf{U}_1 \mathbf{S}_1 \mathbf{V}_1^T \\ \mathbf{\Gamma}_i^{Orthogonal} &\square \mathbf{U}_1 \end{aligned}$$

## Approach 2: Oblique Projection:

$$\begin{aligned} \mathbf{O}_{(k)}^{Oblique} &= (\mathbf{Y}_{f(k)} /_{U_{f(k)}} \mathbf{\Xi}_{p(k)}) /_{U_{f(k)}}^\perp = \mathbf{\Gamma}_i \cdot \mathbf{X}_f /_{U_{f(k)}}^\perp \\ &= \mathbf{USV}^T = [\mathbf{U}_1 \quad \mathbf{U}_2] \begin{bmatrix} S_1 & 0 \\ 0 & S_2 \approx 0 \end{bmatrix} \begin{bmatrix} \mathbf{V}_1^T \\ \mathbf{V}_2^T \end{bmatrix} \approx \mathbf{U}_1 \mathbf{S}_1 \mathbf{V}_1^T \rightarrow \mathbf{\Gamma}_i^{Oblique} \square \mathbf{U}_1 \end{aligned}$$

Multi-variable Output Error State sPace algorithm

Extended observability matrix  $\mathbf{\Gamma}_i \equiv \begin{bmatrix} \mathbf{C}_c \\ \mathbf{C}_c \mathbf{A}_d \\ \mathbf{C}_c \mathbf{A}_d^2 \\ \vdots \\ \mathbf{C}_c \mathbf{A}_d^{i-1} \end{bmatrix} \in \mathbb{R}^{li \times 2n}$

$$\begin{bmatrix} \mathbf{U}_{f(k)} \\ \mathbf{\Xi}_{p(k)} \\ \mathbf{Y}_{f(k)} \end{bmatrix}_{2i(m+l) \times j} = \begin{bmatrix} \mathbf{L}_{11(k)} & \mathbf{0} & \mathbf{0} \\ \mathbf{L}_{21(k)} & \mathbf{L}_{22(k)} & \mathbf{0} \\ \mathbf{L}_{31(k)} & \mathbf{L}_{32(k)} & \mathbf{L}_{33(k)} \end{bmatrix}_{2i(m+l) \times 2i(m+l)} \cdot \begin{bmatrix} \mathbf{Q}_{1(k)}^T \\ \mathbf{Q}_{2(k)}^T \\ \mathbf{Q}_{3(k)}^T \end{bmatrix}_{2i(m+l) \times j}$$

$$\mathbf{O}_{(k)}^{Oblique} = \mathbf{Y}_{f(k)} /_{U_{f(k)}} \mathbf{\Xi}_{p(k)} /_{U_{f(k)}}^\perp = \mathbf{L}_{32(k)} \mathbf{Q}_{2(k)}^T$$

Oblique Projection

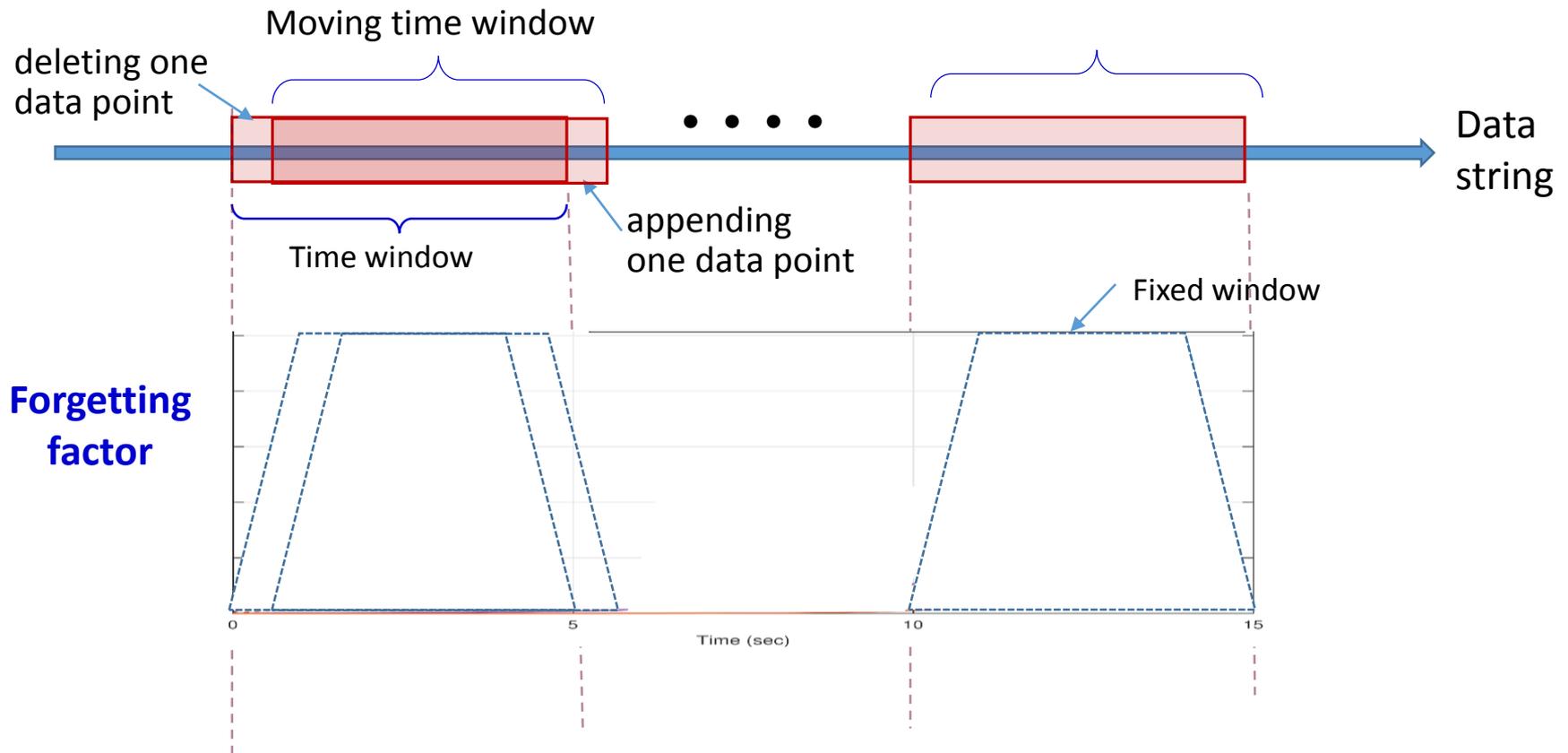


- (1) Direct expansion
- (2) LQ - decomposition



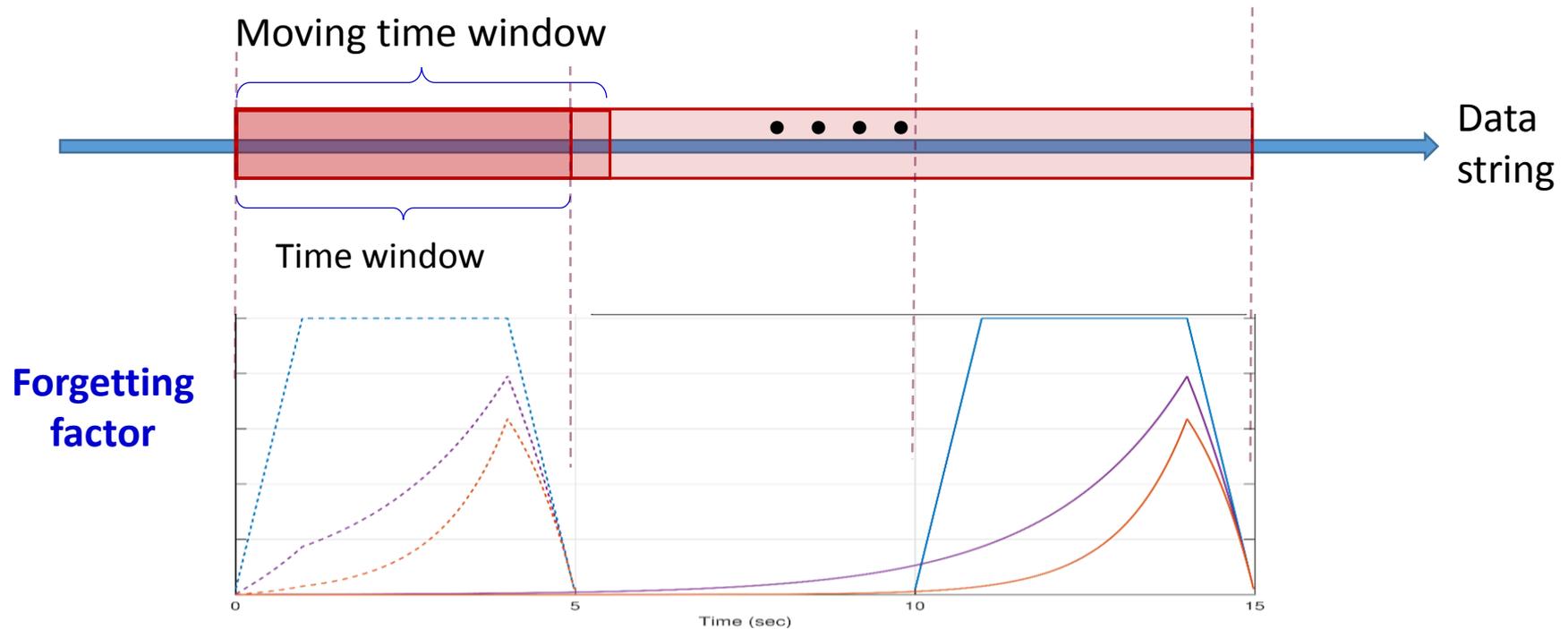
# Recursive Identification (with/without forgetting factor)

## Method 1 (BonaFide RSI): Fixed-length window

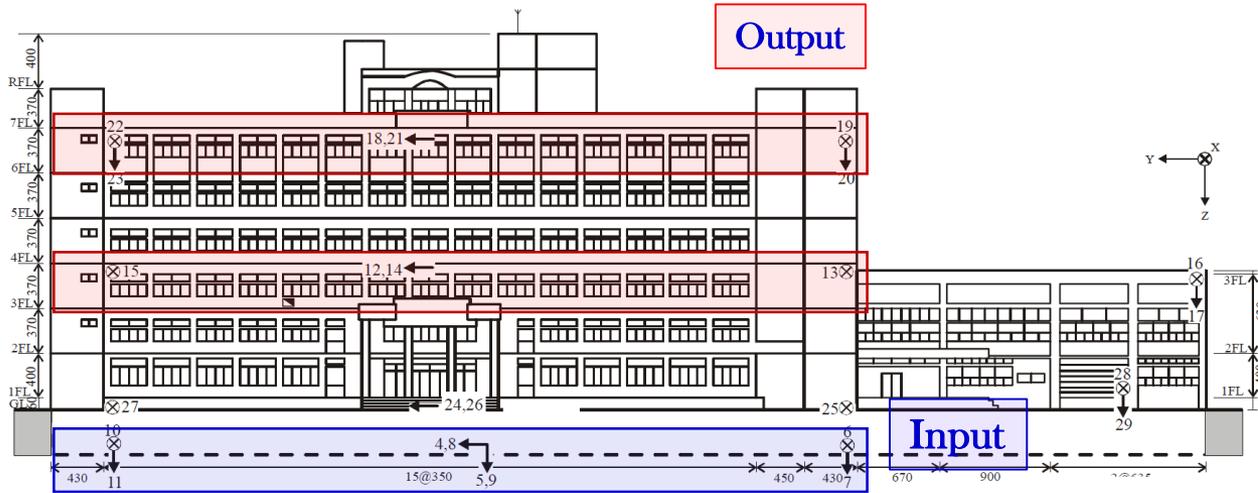


# Recursive Identification (with/without forgetting factor)

## Method 2: Enlarged-length window



# CASE 1 Study: Damage Assessment of Building Structure Using RSI



**Structural Type :**

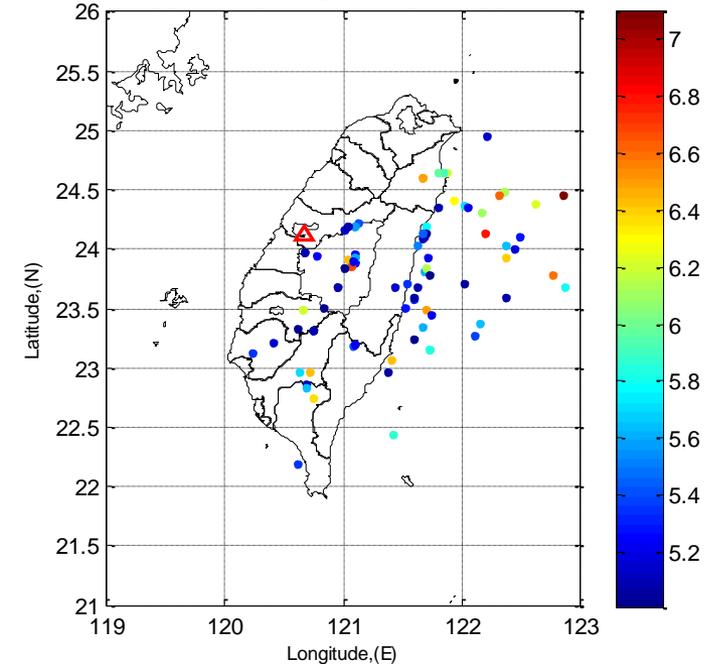
7-story with one story of basement  
RC building with wall and open core

**Total number of channels:**

**29 ( INCLUDING FREE FIELD )**

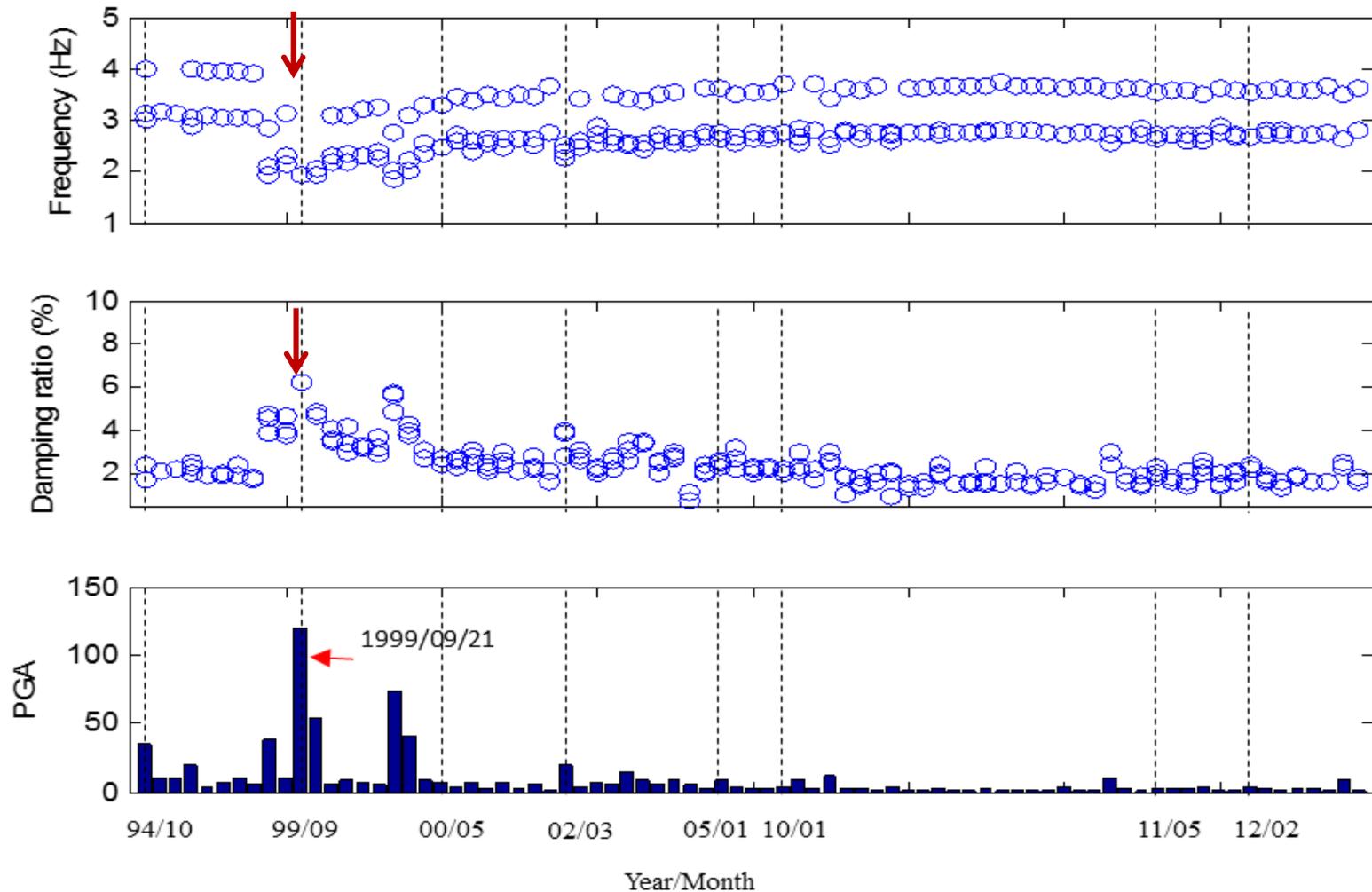


95 Events, Magnitude Distribution

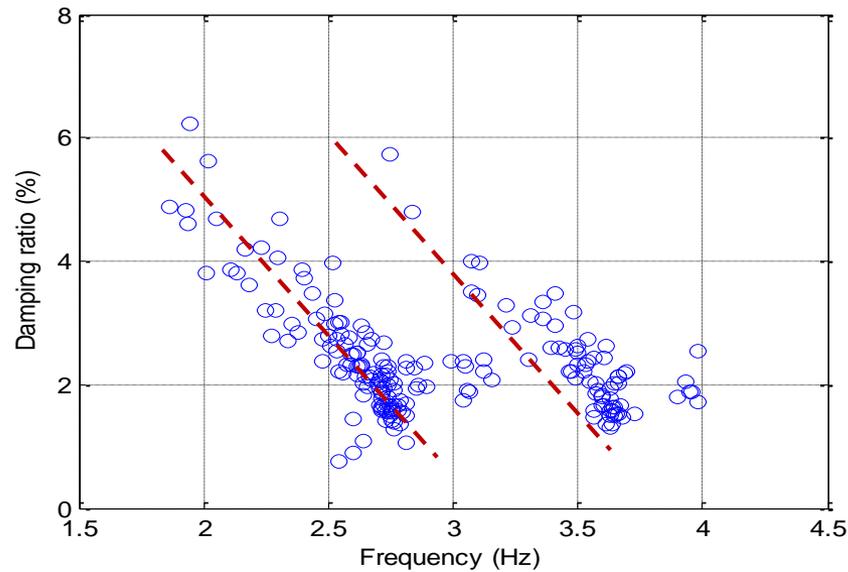
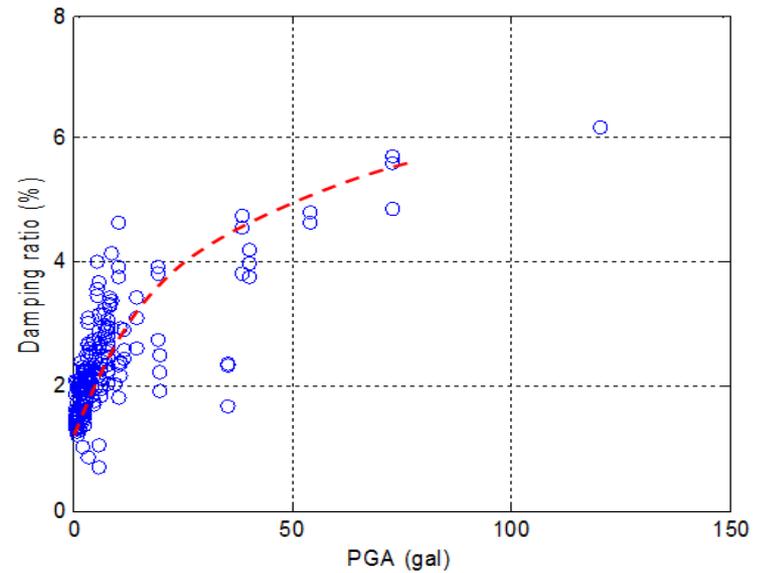
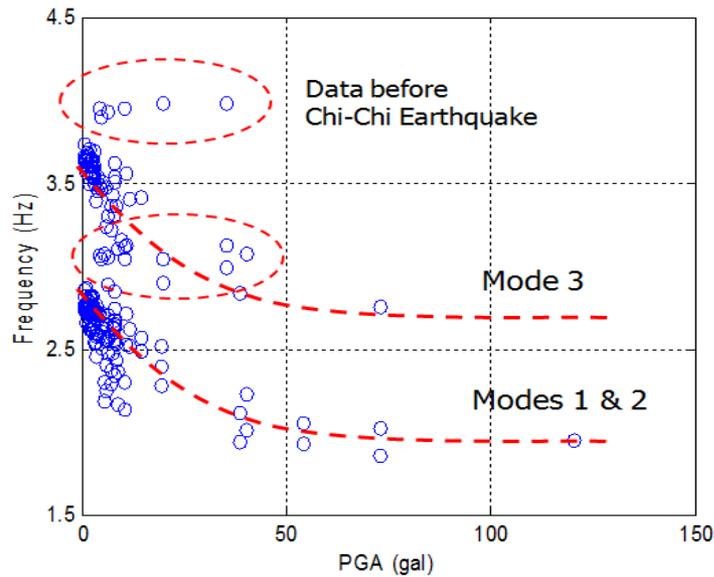


## CE-NCHU Building

1994 ~ 2013 : 79 events



# Damage Assessment of Building Structure Using RSI



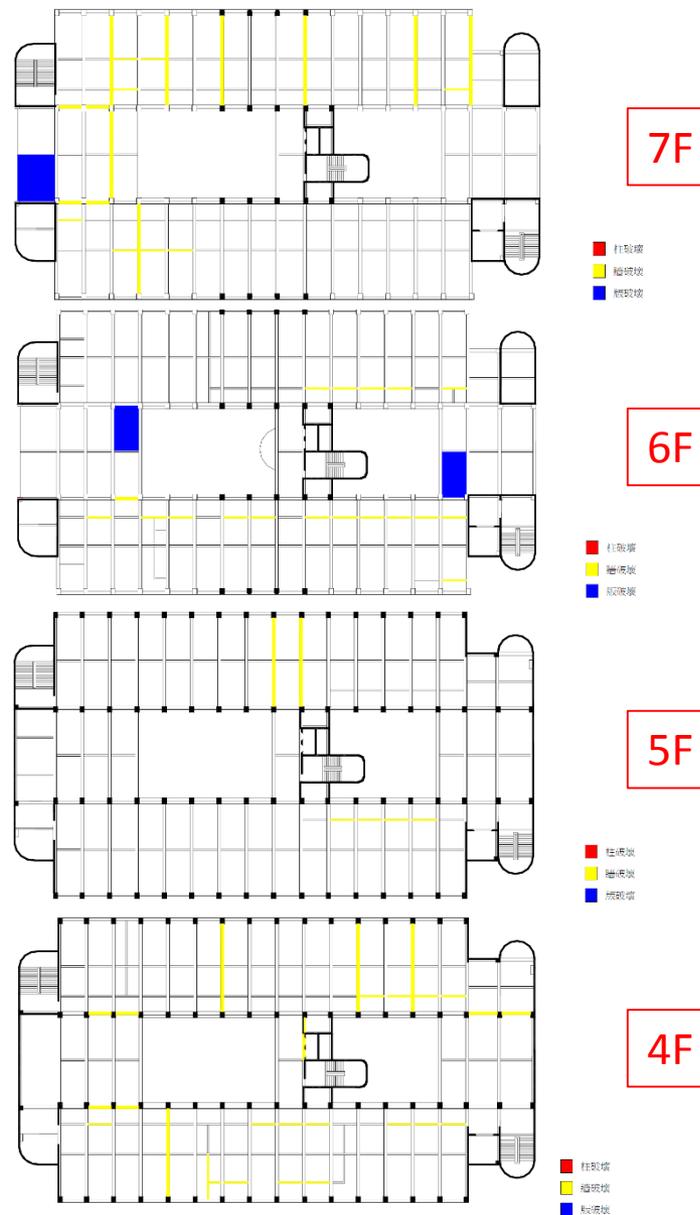
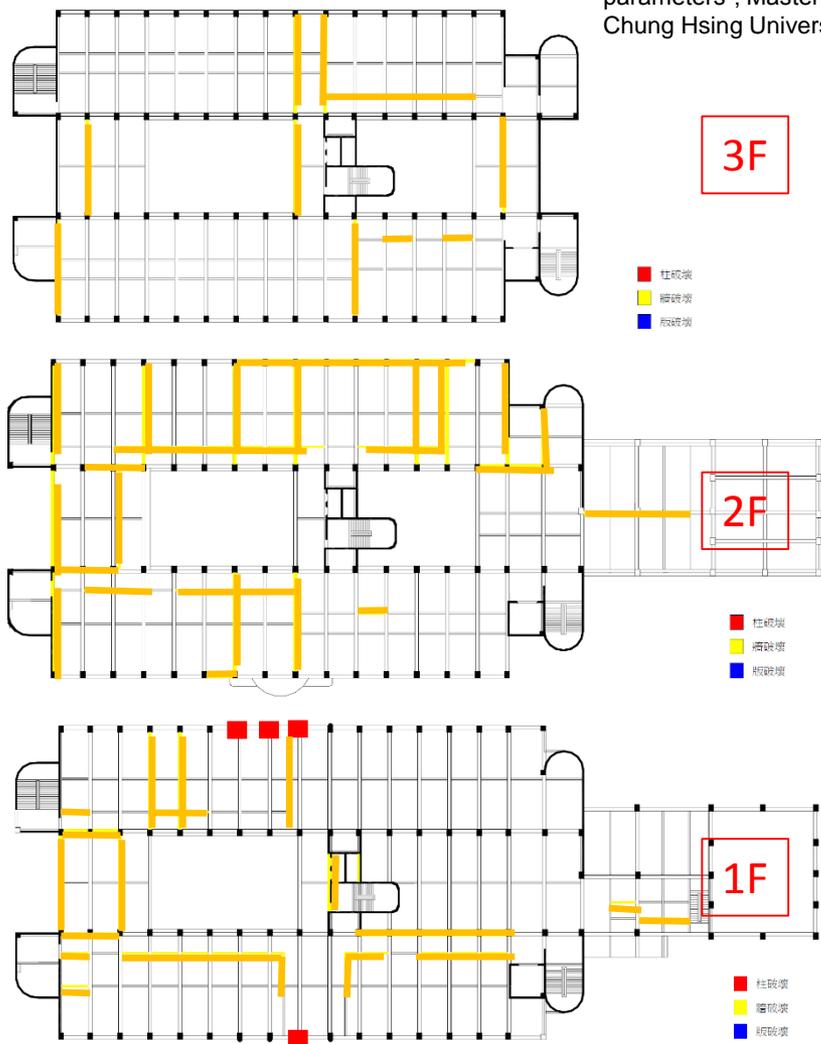
# Damage Assessment of Building Structure Using RSI

■ Damage on column

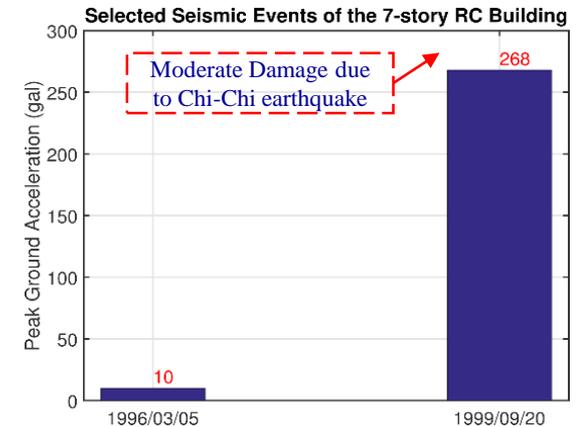
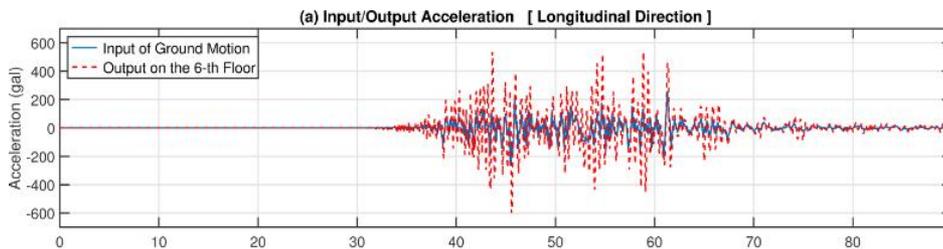
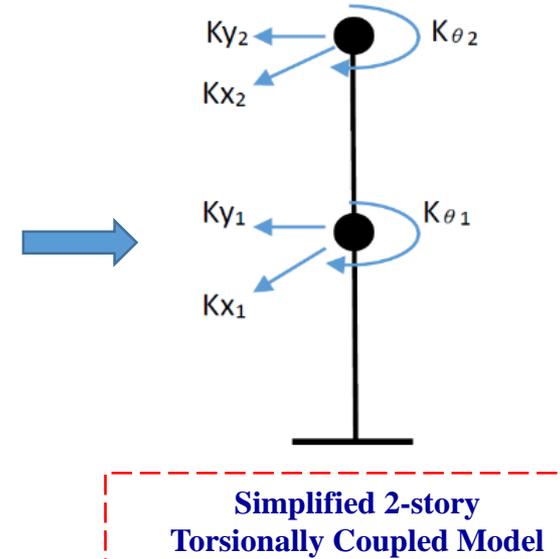
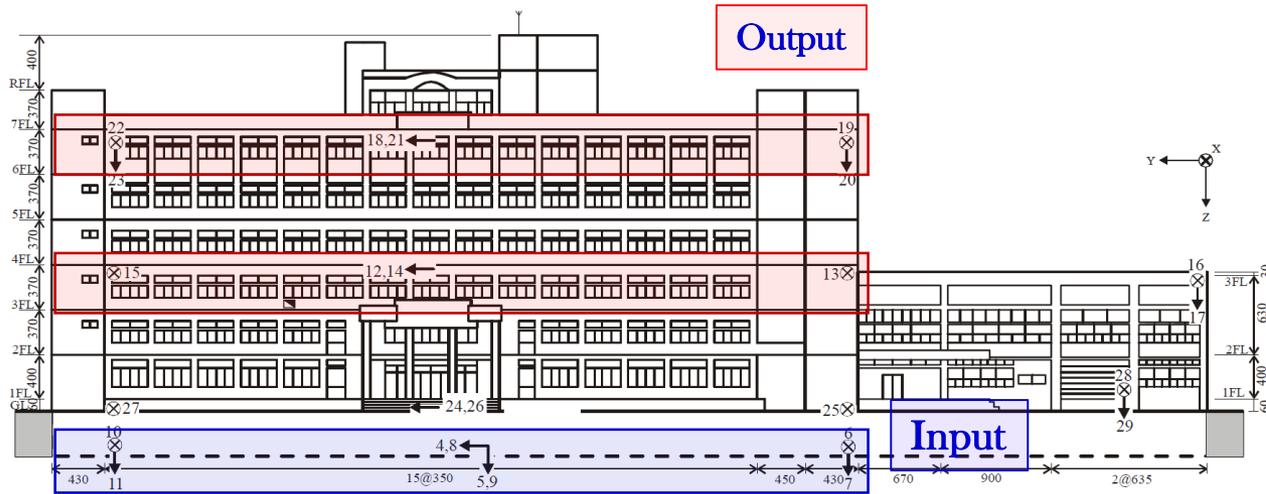
■ Damage on slab

■ Damage on wall

Ref: S.M. Yen, "Story damage index for buildings based on identified modal parameters", Master thesis of National Chung Hsing University (2005).



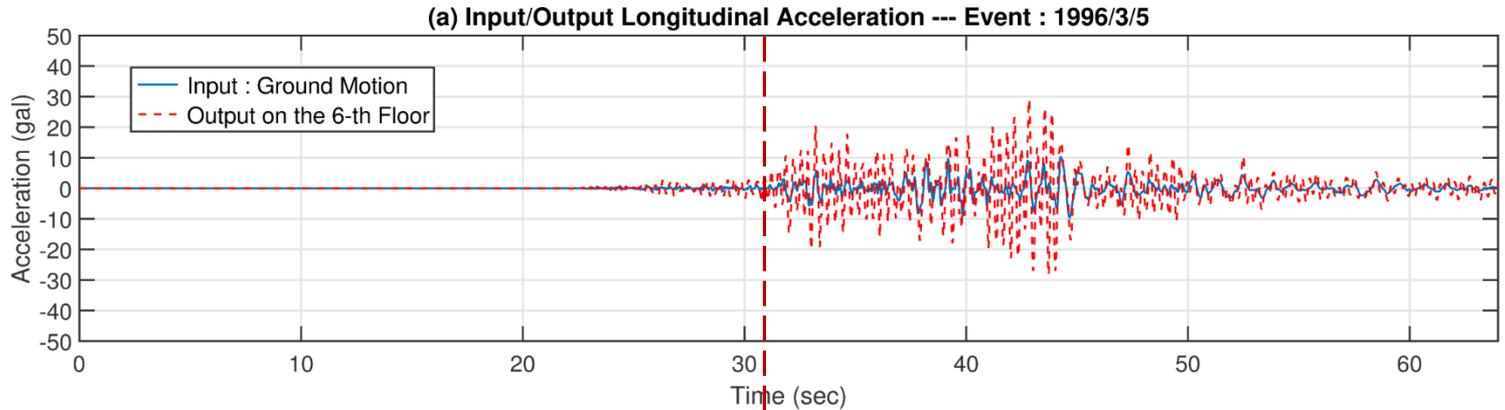
# CASE 1 Study: Damage Assessment of Building Structure Using RSI



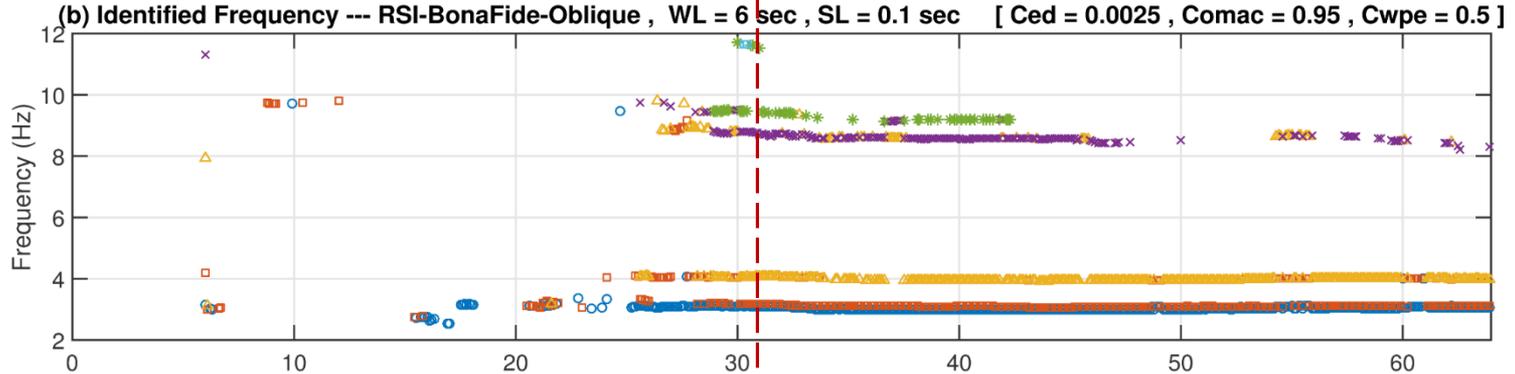
# Damage Assessment of Building Structure Using RSI

1996-3-5 EQ

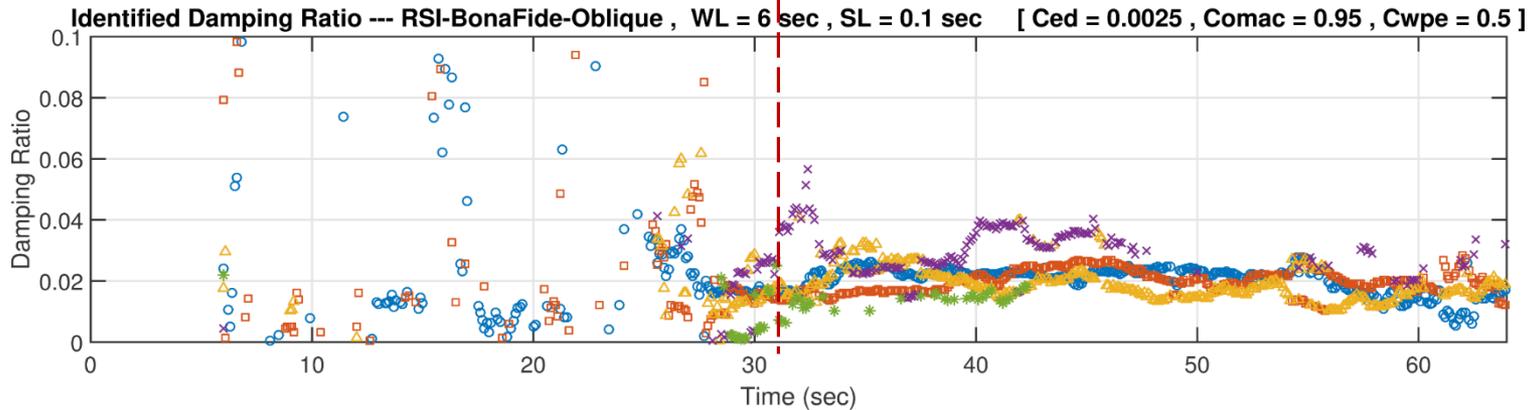
Measurements of small-scale event



Frequency (Hz)



Damping Ratio

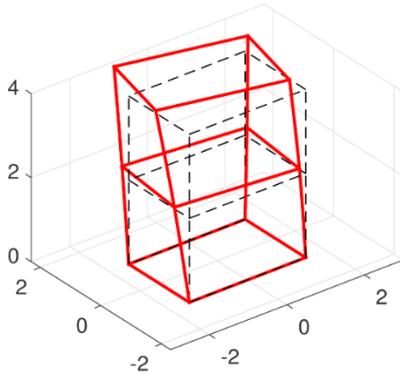


# Damage Assessment of Building Structure Using RSI

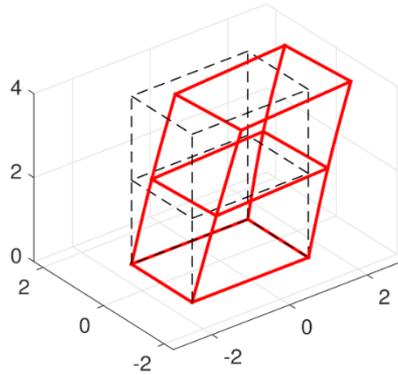
Mode Shapes at time = 30.3 sec. in the small-scale seismic event

[ Event-1996/3/5 : PGA = 10 gal ] RSI-BonaFide Identified Mode Shapes at Time = 30.3 sec.

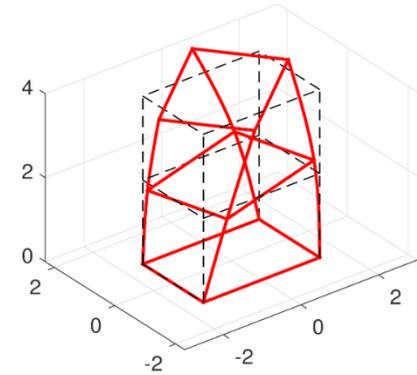
Mode - 1 : 3.1039 Hz



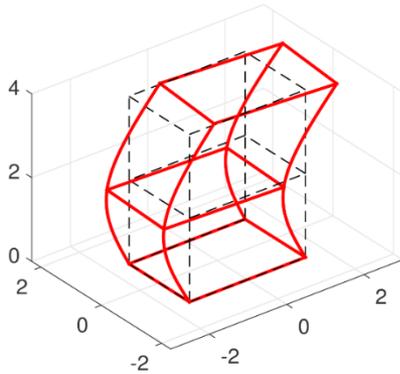
Mode - 2 : 3.176 Hz



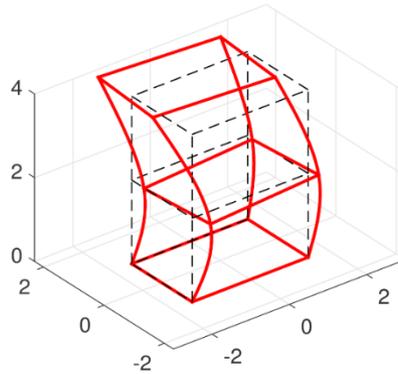
Mode - 3 : 4.0516 Hz



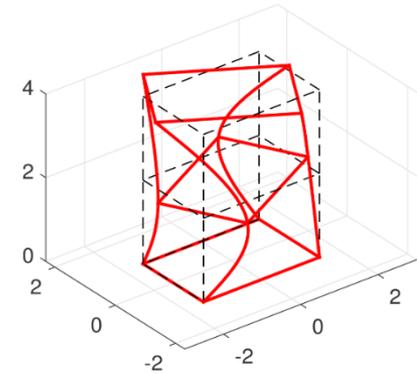
Mode - 4 : 8.8082 Hz



Mode - 5 : 9.4701 Hz



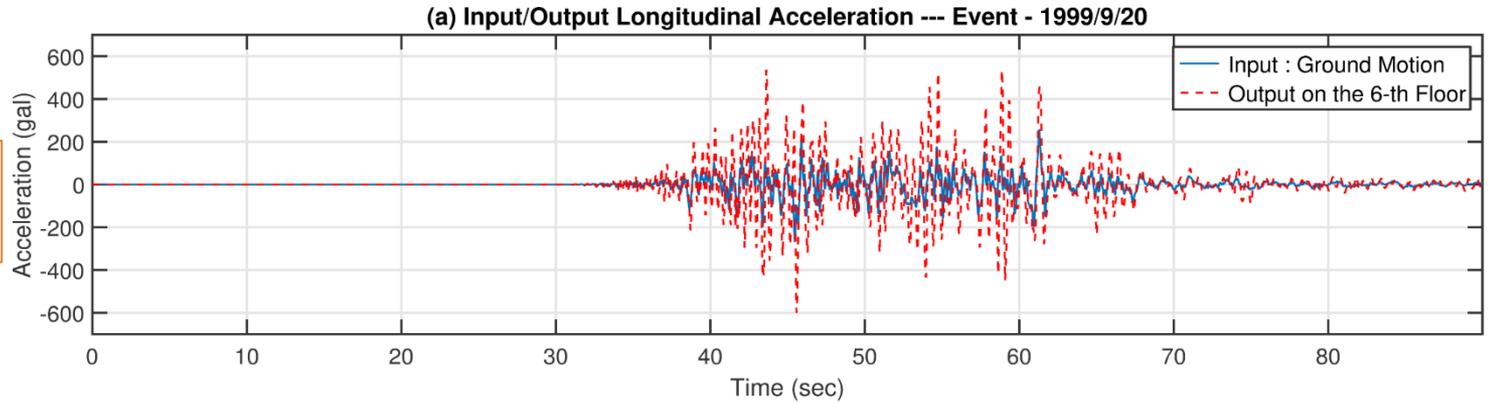
Mode - 6 : 11.6566 Hz



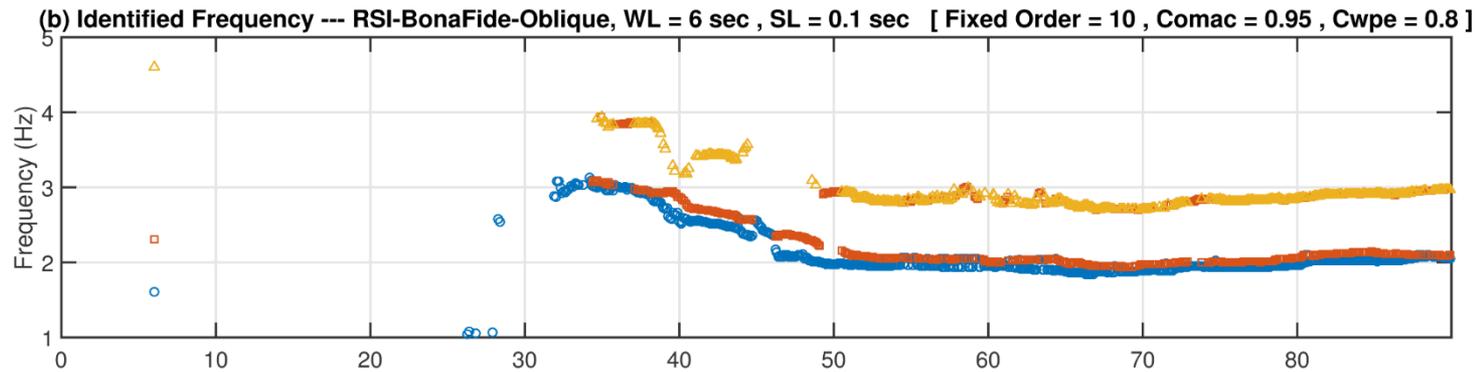
# Damage Assessment of Building Structure Using RSI

1999-9-20 EQ

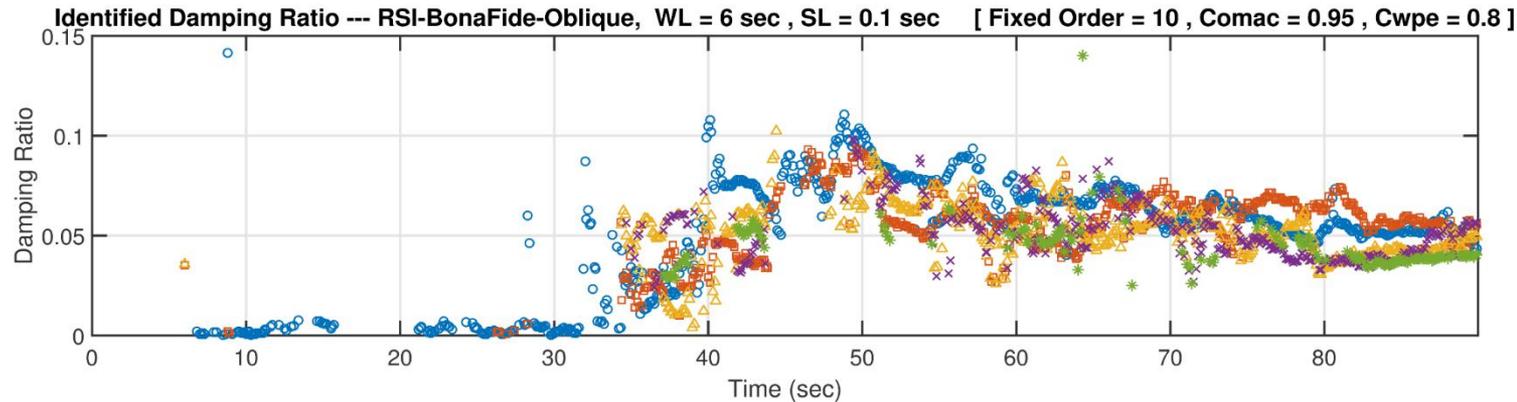
Measurements of  
Chi-Chi earthquake



Frequency (Hz)

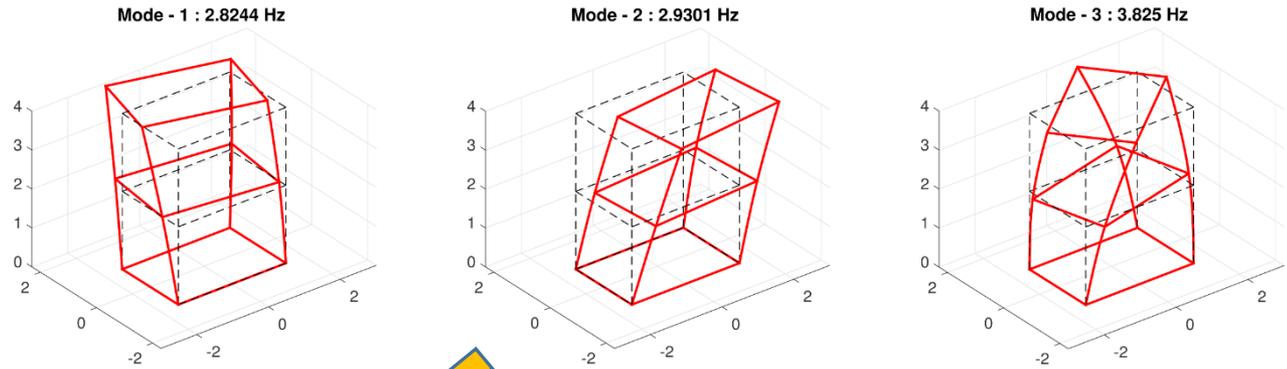


Damping Ratio

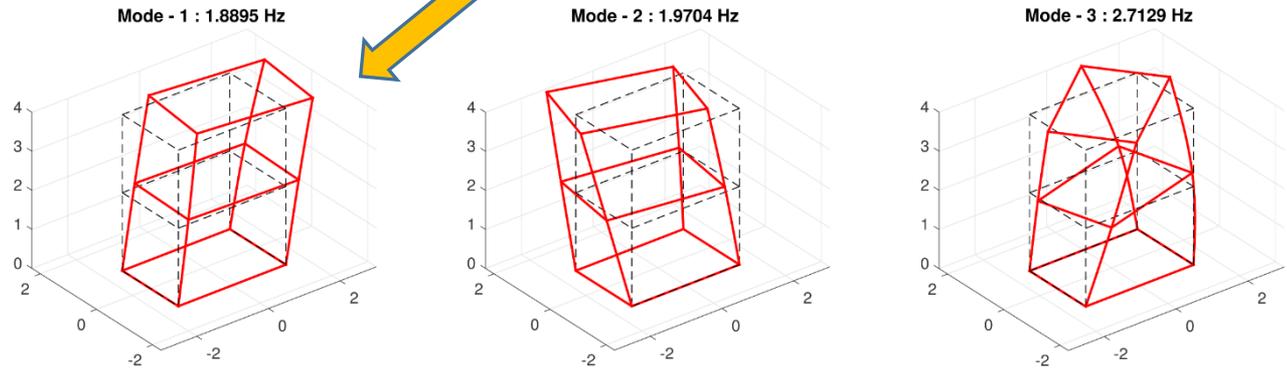


# Damage Assessment of Building Structure Using RSI

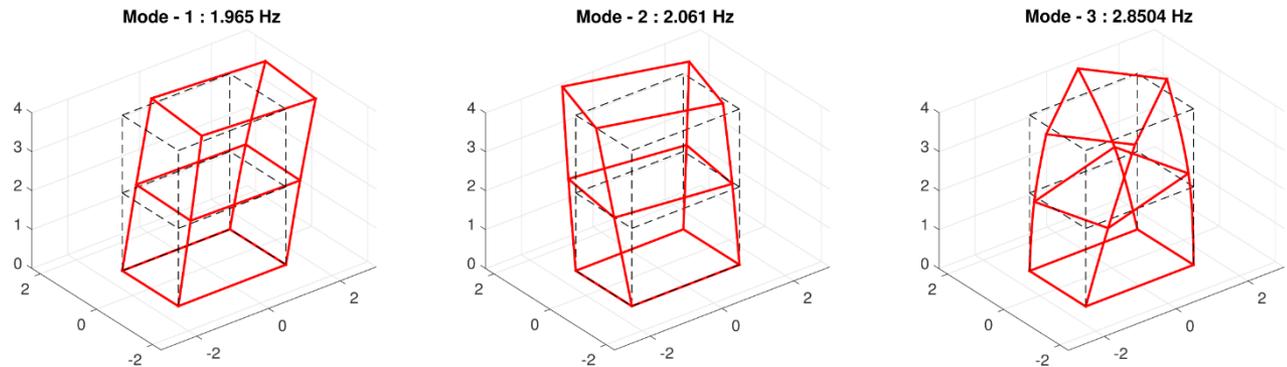
Time at 38.5 sec.  
(Before Strong Motion)



Time at 70.0 sec.  
(After Strong Motion)

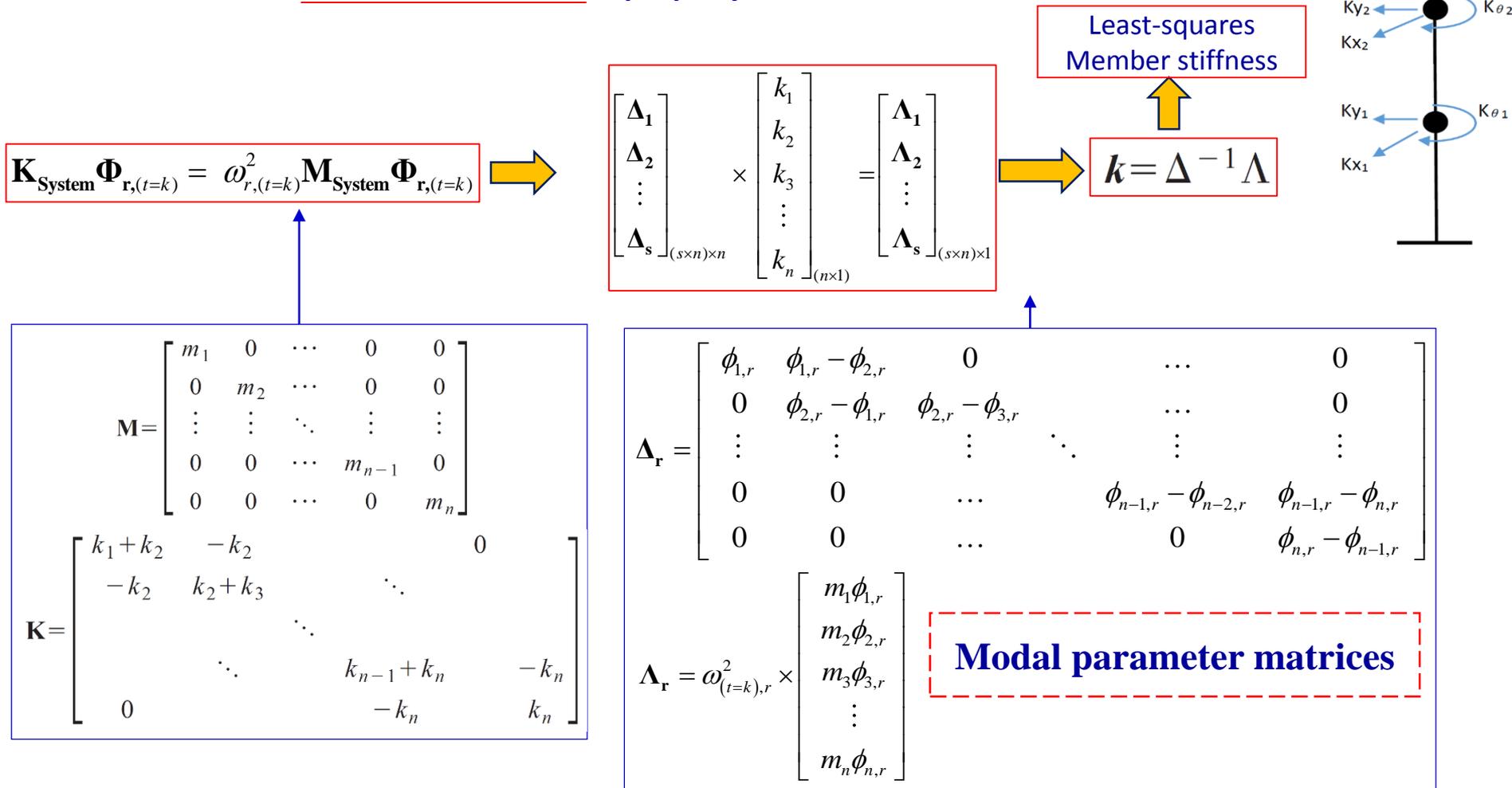


Time at 80.0 sec.  
(After Strong Motion)



# (1) Least Squares Stiffness Method (LSSM)

- Once modal frequencies and mode shapes are identified by RSI-BonaFide, and information of mass is properly assumed...



Ref: J. M. Caicedo, S.J. Dyke and E. A. Johnson. (2004),

Natural excitation technique and eigensystem realization algorithm for phase I of the IASC-ASCE benchmark problem: simulated data, Journal of Engineering Mechanics, Vol.130, No.1, p49-60.



## (2) Efficient Model Correction Method (EMCM)

➤ Input:

- (1) Nominal Mass & Stiffness Matrix
- (2) Modal Frequencies & Mode Shapes

**Efficient Model Correction Method (EMCM)**

➤ Output:

Updated Mass & Stiffness Matrix

(1) Symmetry of updated matrices

$$M_{update} = M_{update}^T$$

$$K_{update} = K_{update}^T$$

(2) Orthogonality of updated matrices

$$\Phi_{r,update}^T \cdot M_{update} \cdot \Phi_{p,update} = \delta_{r,p}$$

$$\Phi_{r,update}^T \cdot K_{update} \cdot \Phi_{p,update} = \begin{cases} \hat{\omega}_r^2 \cdot \delta_{r,p} \\ \omega_r^2 \cdot \delta_{r,p} \end{cases}$$

(3) Satisfaction of Eigen-equation  
[Model Error = 0]

$$K_{update} \cdot \hat{\Phi}_r - \hat{\omega}_r^2 \cdot M_{update} \cdot \hat{\Phi}_r = 0$$

Constructing the M-orthogonal basis vectors : G matrix  
(Gram-Schmidt orthogonalization process for unmeasured mode shapes  $v_r^*$  )

$$G = \begin{cases} g_r = \Phi_{(k),r} & , r = 1, 2, \dots, s \\ g_r = v_r^* & , r = s + 1, \dots, N_{total\_DOFs} \end{cases}$$

Calculating the inverse of transformation matrix :  $R^{-1}$  matrix

$$R^{-1} = G \cdot [\hat{\Phi}_{(k),1} \quad \hat{\Phi}_{(k),2} \quad \dots \quad \hat{\Phi}_{(k),s} \quad g_{s+1} \quad \dots \quad g_{total\_DOFs}]^{-1}$$

Correcting the mass matrix :  $M^{update}$  matrix

$$M^{update} = (R^{-1})^T \cdot M \cdot R^{-1}$$

Pre-correcting the stiffness matrix :  $K^*$  matrix

$$K^* = (R^{-1})^T \cdot K \cdot R^{-1}$$

Correcting the stiffness matrix :  $K^{update}$  matrix

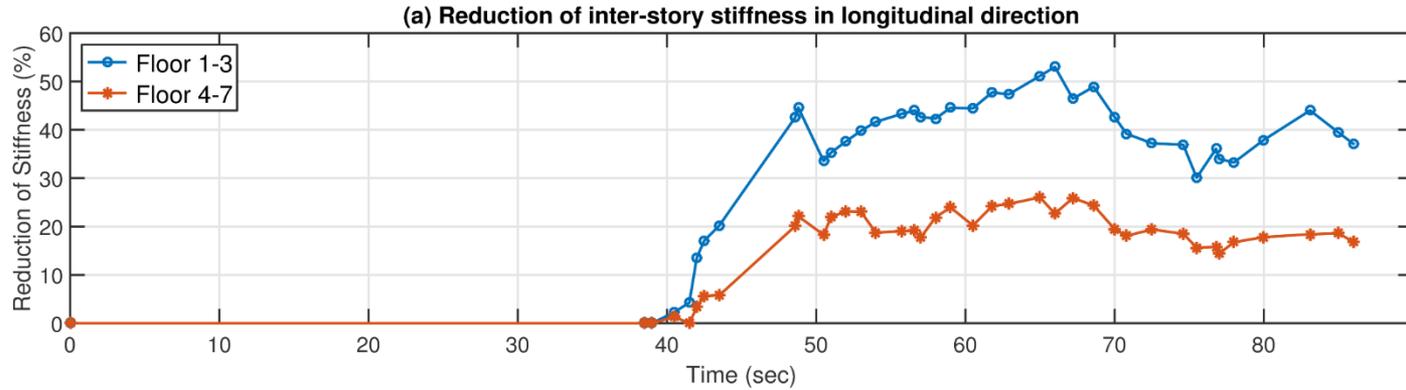
$$K^{update} = K^* + M^{update} \cdot \left[ \sum_{r=1}^s (\hat{\omega}_r^2 - \omega_r^2) \cdot \hat{\Phi}_{(k),r} \cdot \hat{\Phi}_{(k),r}^T \right] \cdot M^{update}$$

Ref: K.V. Yuen, "Efficient model correction method with modal measurement," Journal of Engineering Mechanics, Vol. 136, No. 1, 91-99 (2010).

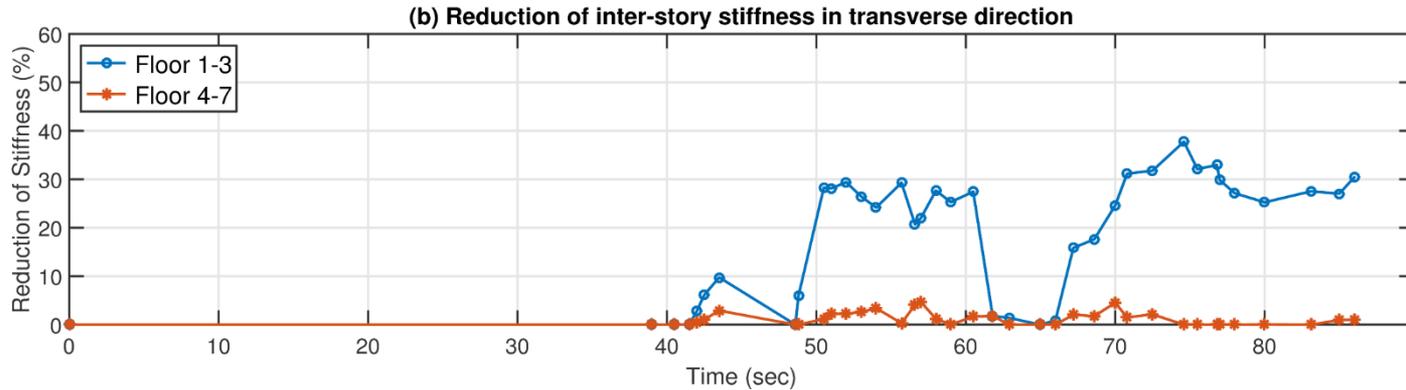


# Damage Assessment of Building Structure Using RSI

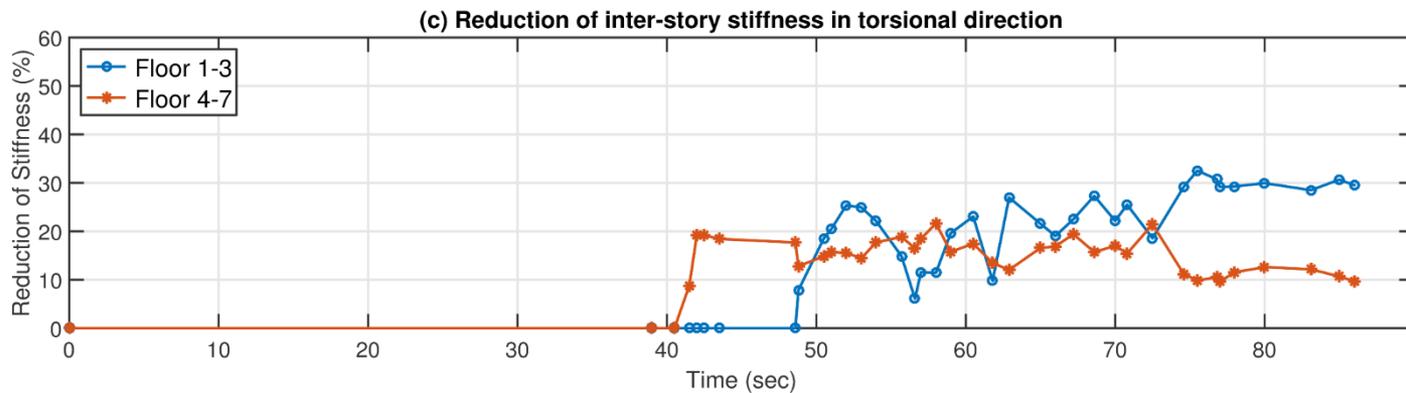
Reduction of Longitudinal Stiffness (%)



Reduction of Transverse Stiffness (%)



Reduction of Torsional Stiffness (%)



# Estimation of Computation Time

<i>Computational Time per Identification using traditional LQ decomposition</i>						
RSI-Procedure	Preprocess	Projection (Oblique)	Eigen-value Decomp.	Parameter Extraction	Computational Time	
Mean (sec.)	0.0194	0.0192	0.0249	0.0046	$\mu$	0.0681
STD (sec.)	0.0104	0.0025	0.0041	0.0011	$\mu + 2\sigma$	<b>0.1043</b>



<i>Computational Time per Identification using RSI-BonaFide-OBL</i>						
RSI-Procedure	Preprocess	Projection (Oblique)	Eigen-value Decomp.	Parameter Extraction	Computational Time	
Initial Conduction	0.0194	0.0252	0.0101	0.0061	0.0608	
Updating Method	<i>Bona-Fide L32 renewing algorithm</i>					
Mean (sec.)	0.0194	0.0050	0.0251	0.0046	$\mu$	0.0541
STD (sec.)	0.0104	0.0005	0.0043	0.0012	$\mu + 2\sigma$	<b>0.0869</b>



<i>Computational Time per Identification using RSI-Inversion-OBL</i>						
RSI-Procedure	Preprocess	Projection (Oblique)	Eigen-value Decomp.	Parameter Extraction	Computational Time	
Initial Conduction	0.0194	0.3149	0.0314	0.0129	0.3786	
Updating Method	<i>Inversion-Oblique Projection renewing algorithm</i>					
Mean (sec.)	0.0194	0.0032	0.0259	0.0048	$\mu$	0.0533
STD (sec.)	0.0104	0.0004	0.0041	0.0016	$\mu + 2\sigma$	<b>0.0863</b>



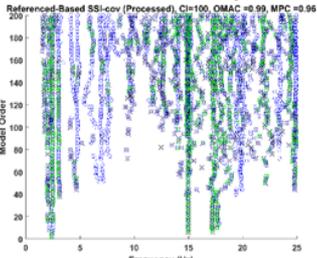
**Less Than Shifting Length = 0.1 sec**



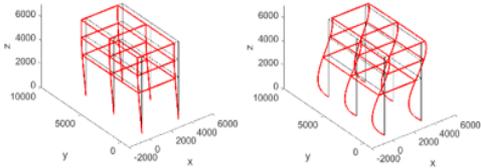
# NCREE-South Center Grand Opening Shaking Table Test

## WN1-test

### SSI-COV analysis

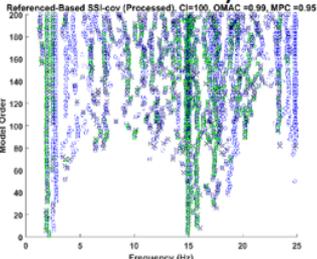


mode 1: Freq = 2.517Hz, Damp. Ratio = 6.692%    mode 2: Freq = 14.979Hz, Damp. Ratio = 1.752%

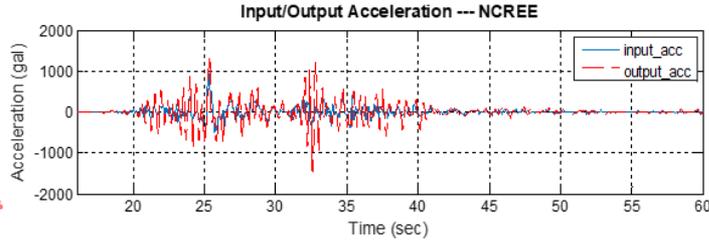
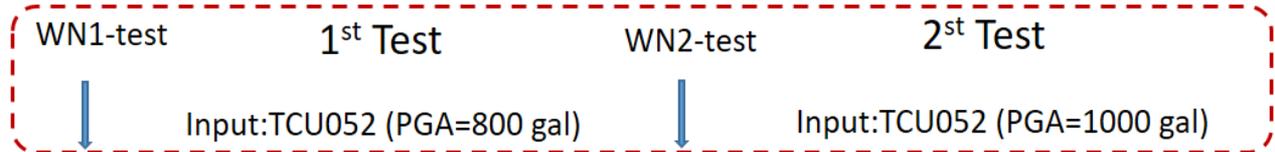
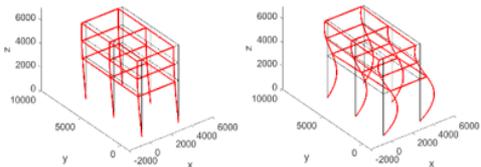


## WN2-test

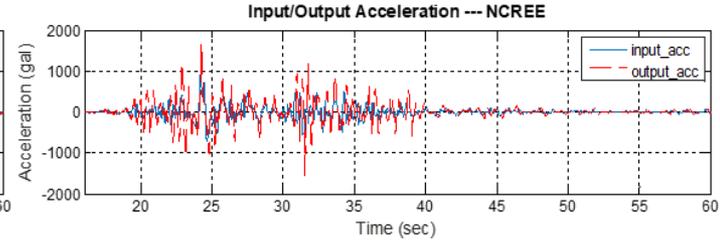
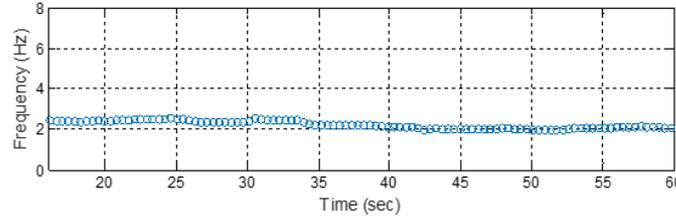
### SSI-COV analysis



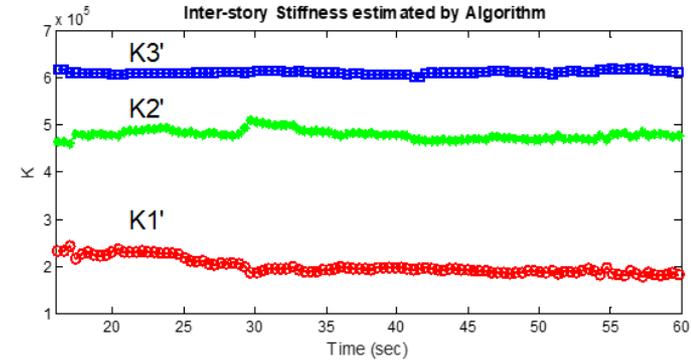
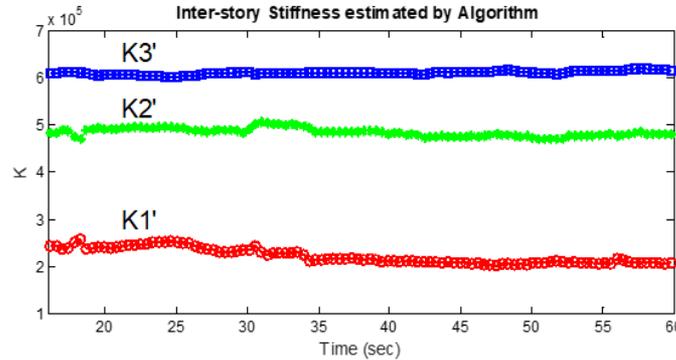
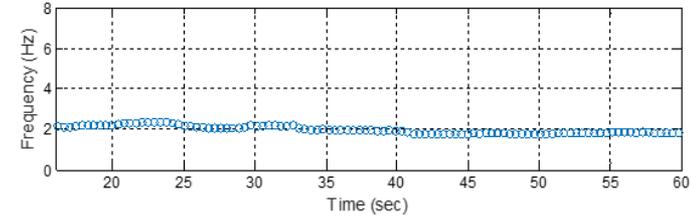
mode 1: Freq = 1.949Hz, Damp. Ratio = 7.440%    mode 2: Freq = 15.001Hz, Damp. Ratio = 0.545%



Identified Frequency -- RSI-BonaFide-Oblique, WL = 4 sec, SL = 0.4 sec



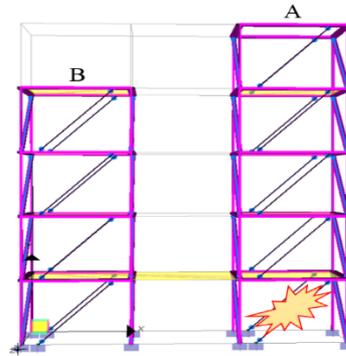
Identified Frequency -- RSI-BonaFide-Oblique, WL = 4 sec, SL = 0.4 sec



NCREE-South Test	Estimated stiffness (KN/m)			
	Initial	Minimum	Final	% of reduction
800 gal excitation	$2.28 \times 10^4$	$1.87 \times 10^4$	$1.93 \times 10^4$	15.4%
1000 gal excitation	$2.18 \times 10^4$	$1.66 \times 10^4$	$1.71 \times 10^4$	21.6% (25%)

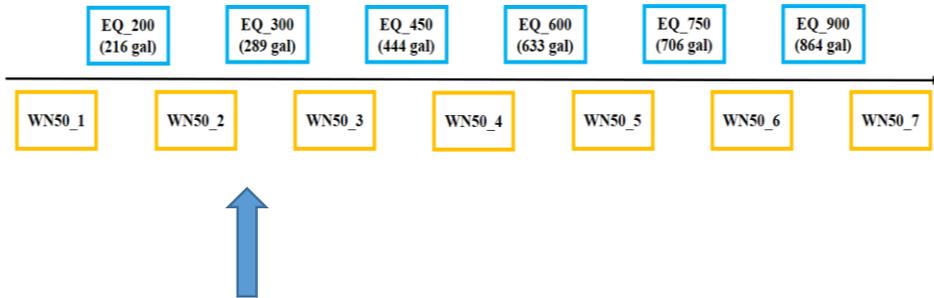
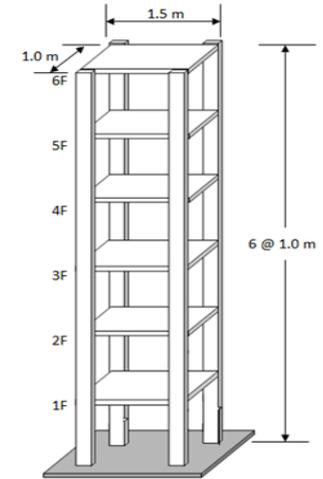


# Damage Detection & Localization



(a) Weak bracing at the 1<sup>st</sup> FL of A.

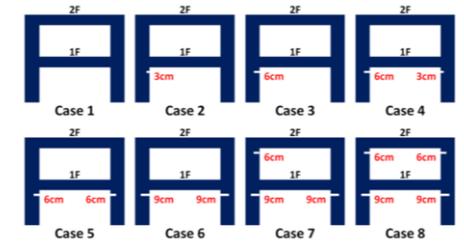
Brace1 Dimension: 19 mm × 1.2 mm (weak)  
 Brace2 Dimension: 21.3 mm × 2 mm (normal)  
 Dimension of each floor: 1.1 m × 1.5 m × 1.17 m



Floor	Damage Cases							
	Case 1	Case 2	Case 3	Case 4	Case 5	Case 6	Case 7	Case 8
6 <sup>th</sup> FL	-	-	-	-	-	-	-	-
5 <sup>th</sup> FL	-	-	-	-	-	-	-	-
4 <sup>th</sup> FL	-	-	-	-	-	-	-	-
3 <sup>rd</sup> FL	-	-	-	-	-	-	-	-
2 <sup>nd</sup> FL	-	-	-	-	-	-	Cut a <sub>6</sub>	Cut a <sub>6</sub> and b <sub>6</sub>
1 <sup>st</sup> FL	Cut a <sub>3</sub>	Cut a <sub>6</sub>	Cut a <sub>6</sub> and b <sub>3</sub>	Cut a <sub>6</sub> and b <sub>6</sub>	Cut a <sub>9</sub> and b <sub>9</sub>			

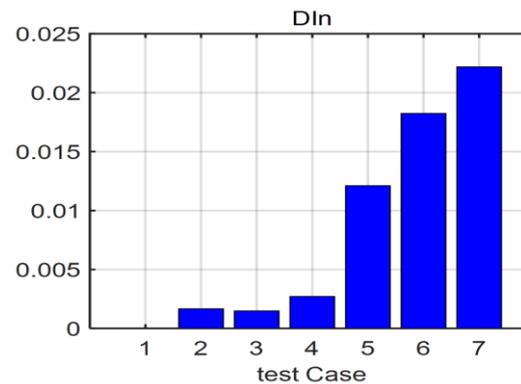
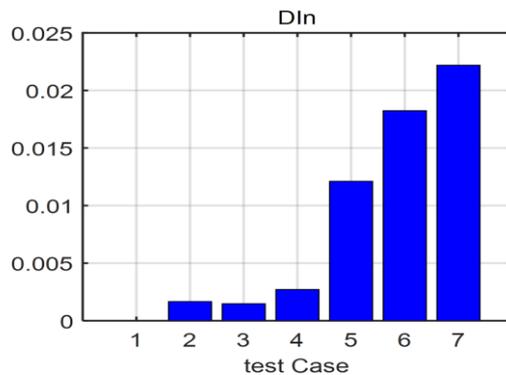
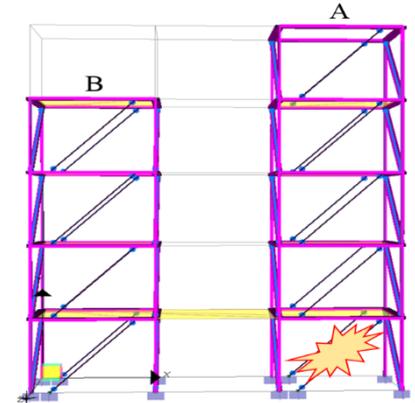
Structure damaged in Lower modes

Structure damaged in higher modes

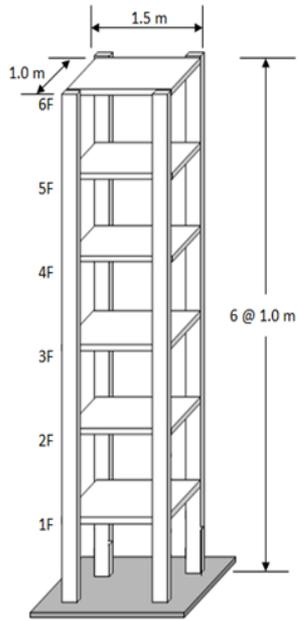


# Results from SSI-COV (ambient data)

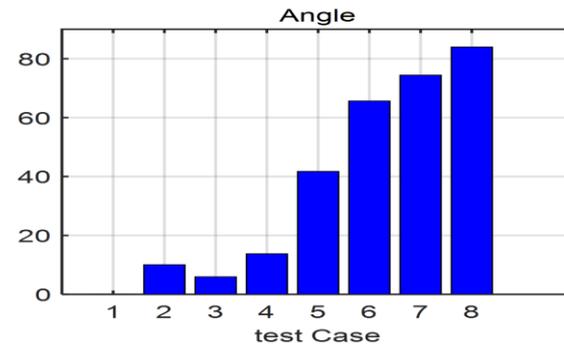
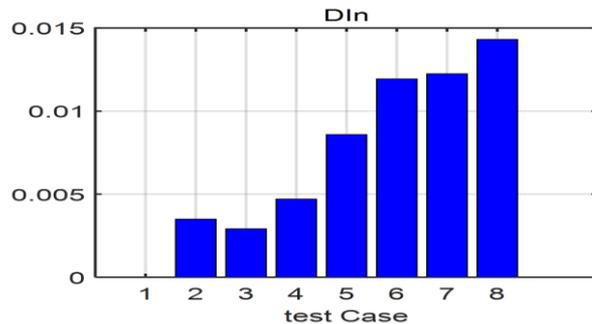
Freq.(Hz)	Case 1	Case 2	Case 3	Case 4	Case 5	Case 6	Case 7
Mode 1	4.917	4.899	4.896	4.872	3.251	2.329	1.744
Mode 2	7.133	7.112	7.143	7.130	6.655	6.559	6.502
Mode 3	15.434	15.398	15.418	15.326	11.860	11.056	10.646
Mode 4	20.770	20.782	20.757	20.748	20.362	20.417	20.224
Mode 5	21.843	21.749	21.855	21.768	21.252	21.010	22.399
Mode 6	27.817	27.817	27.712	27.780	27.782	27.464	27.238
Mode 7	33.775	33.655	32.647	32.868	32.823	32.745	38.072
Mode 8	38.511	38.028	37.750	37.597	37.631	37.760	34.574
Mode 9	39.978	39.534	38.361	38.422	39.198	38.966	38.864



# Results from SSI-COV (ambient data)

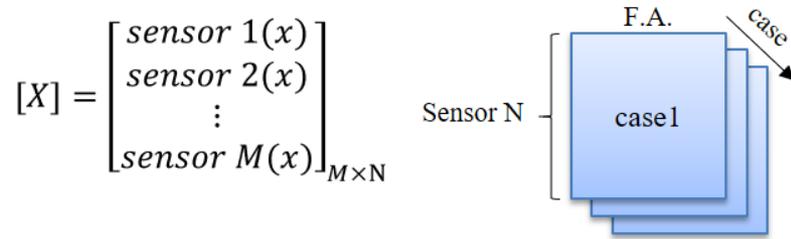


Freq.(Hz)	Case 1	Case 2	Case 3	Case 4	Case 5	Case 6	Case 7	Case 8
Mode 1	1.141	1.139	1.137	1.136	1.138	1.133	1.131	1.129
Mode 2	2.224	2.211	2.203	2.200	2.201	2.197	2.190	2.187
Mode 3	3.632	3.628	3.615	3.612	3.602	3.587	3.579	3.576
Mode 4	6.299	6.295	6.283	6.277	6.267	6.248	6.245	6.244
Mode 5	8.516	8.478	8.463	8.466	8.458	8.451	8.410	8.380
Mode 6	9.189	9.184	9.169	9.162	9.146	9.105	9.091	9.078
Mode 7	10.450	10.420	10.390	10.403	10.399	10.395	10.336	10.309
Mode 8	12.065	12.064	12.049	12.041	12.032	11.979	11.950	11.933
Mode 9	14.313	14.309	14.299	14.297	14.295	14.282	14.265	14.245
Mode 10	19.821	19.733	19.631	19.582	19.471	19.125	19.010	18.917
Mode 11	21.949	21.860	21.783	21.753	21.665	21.446	21.355	21.355
Mode 12	27.961	27.954	27.974	27.975	28.019	28.116	28.117	28.114
Mode 13	38.407	38.240	37.914	37.794	37.525	37.054	36.931	36.954
Mode 14	58.419	58.233	57.598	57.294	56.573	54.786	53.778	51.835
Mode 15	60.134	59.917	59.660	59.529	59.494	59.422	59.281	59.225
Mode 16	76.283	76.249	75.989	75.944	75.801	75.289	74.380	73.502
Mode 17	77.928	77.781	77.221	77.143	76.920	76.668	76.682	76.598



# Damage detection & Localization : Sammon Map

## Step 1: Create X matrix (consider to be N-dimensional space)



where M is the number of sensing nodes, N is the number of **discrete Fourier amplitude**. (Time domain data can also be applied.)

## Step 2: Covariance matrix

$$[C]_{M \times M} = \text{cov}(X) = \frac{XX^T}{M-1} \quad \longrightarrow \quad C = \Phi \Lambda \Phi^T$$

## Step 3: Solve for the eigenvalue, eigenvectors of C

$$[\Lambda] = \text{diag}(\lambda_1, \lambda_2, \dots, \lambda_M) \quad \text{where } \lambda_1 > \lambda_2 > \dots > \lambda_M$$

## Step 4a: Project the high-dimensional space onto the 2-D dimensional space

$$[X]_{2D-PCA} = X \cdot [\Phi(\lambda_1, \lambda_2)] \quad \longleftarrow \text{2D-PCA matrix}$$

$$[X]_{2D-PCA} = \begin{bmatrix} x_{11} & x_{12} \\ x_{21} & x_{22} \\ \vdots & \vdots \\ x_{M1} & x_{M2} \end{bmatrix}$$

Euclidean distance:  

$$\delta_{X_i,j} = \sqrt{\sum_{p=1}^2 (X_{i,p} - X_{j,p})^2}$$
 to construct the initial PCA-based map

$$[\Delta_{PCA-map}]_{M \times M} = \begin{bmatrix} 0 & \delta_{X1,2} & \dots & \delta_{X1,M} \\ \delta_{X2,1} & 0 & \dots & \delta_{X2,M} \\ \vdots & \vdots & \ddots & \vdots \\ \delta_{XM,1} & \delta_{XM,2} & \dots & 0 \end{bmatrix}_{M \times M}$$



# Damage detection & Localization : Sammon Map

**Step 4b: To construct the**

$$[X_{Sammon-Map}]_{48 \times 2}$$

Using  $[X] = \begin{bmatrix} \text{sensor 1}(f) \\ \text{sensor 2}(f) \\ \vdots \\ \text{sensor } M(f) \end{bmatrix}_{M \times N}$

$$\varepsilon_{xi,j} = \sqrt{\sum_{k=1}^N ([X_{i,k}] - [X_{j,k}])^2 / N}$$

to construct the initial {X}-based map

$$[\Delta_{\{X\}}]_{M \times M} = \begin{bmatrix} 0 & \varepsilon_{X1,2} & \cdots & \varepsilon_{X1,M} \\ \varepsilon_{X2,1} & 0 & \cdots & \varepsilon_{X2,M} \\ \vdots & \vdots & \ddots & \vdots \\ \varepsilon_{XM,1} & \varepsilon_{XM,2} & \cdots & 0 \end{bmatrix}_{M \times M}$$

**Step 5: Minimization**

From step 4b :

$$[\Delta_{\{X\}}]_{M \times M} = \begin{bmatrix} 0 & \varepsilon_{X1,2} & \cdots & \varepsilon_{X1,M} \\ \varepsilon_{X2,1} & 0 & \cdots & \varepsilon_{X2,M} \\ \vdots & \vdots & \ddots & \vdots \\ \varepsilon_{XM,1} & \varepsilon_{XM,2} & \cdots & 0 \end{bmatrix}_{M \times M}$$

From step 4a :

$$[\Delta_{PCA-map}]_{M \times M} = \begin{bmatrix} 0 & \delta_{X1,2} & \cdots & \delta_{X1,M} \\ \delta_{X2,1} & 0 & \cdots & \delta_{X2,M} \\ \vdots & \vdots & \ddots & \vdots \\ \delta_{XM,1} & \delta_{XM,2} & \cdots & 0 \end{bmatrix}_{M \times M}$$

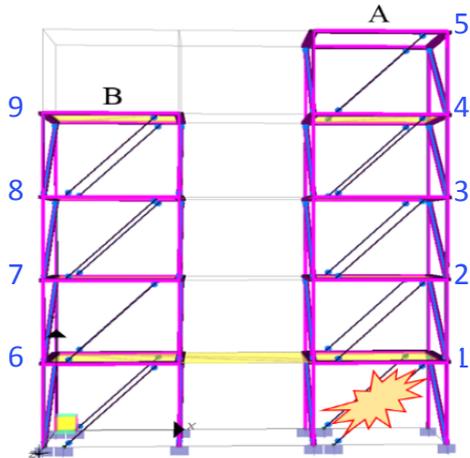
$$E = \frac{1}{\sum_{i < j} \varepsilon_{xi,j}} \sum_{i < j} \frac{(\varepsilon_{xi,j} - \delta_{xi,j})^2}{\varepsilon_{xi,j}} \quad \longrightarrow \quad \text{Minimization}$$

**Then we can get the reduce matrix :**

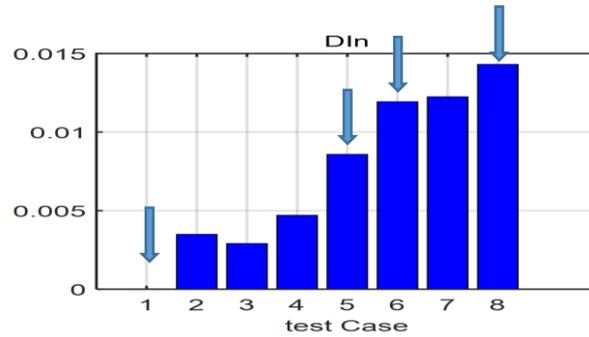
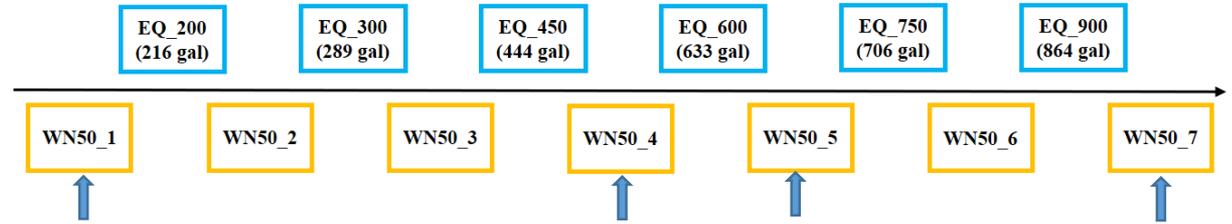
$$[X]_{Sammon Map} = \begin{bmatrix} x_1 & y_1 \\ x_2 & y_2 \\ \vdots & \vdots \\ x_M & y_M \end{bmatrix}$$



# Damage detection & Localization : Sammon Map

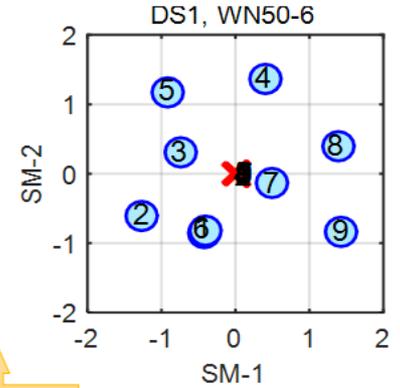
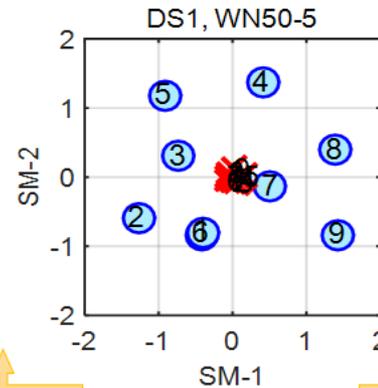
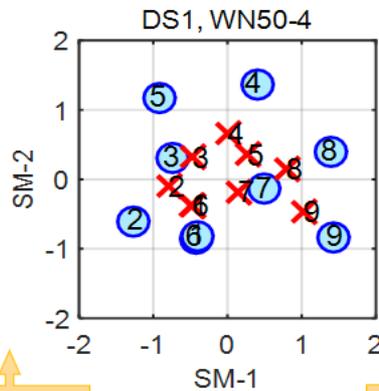
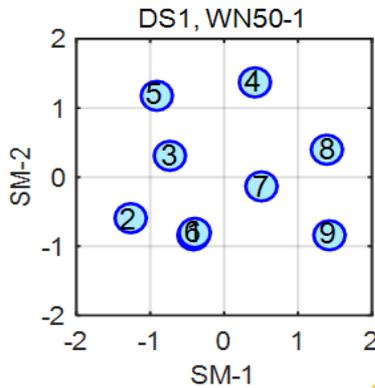


Damage Scenario 1



Scenario 1

Reference



EQ450

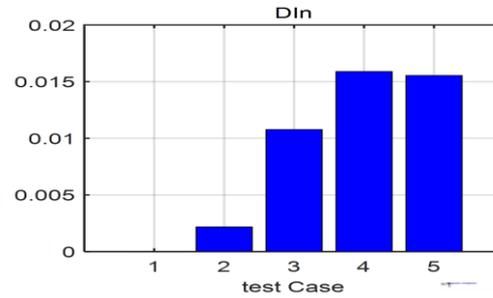
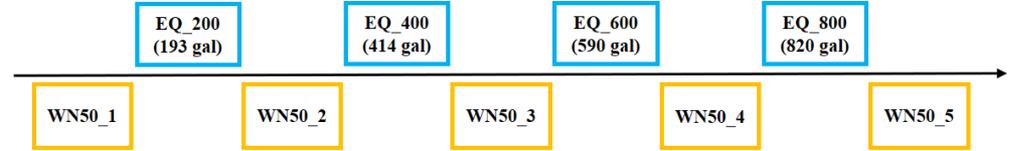
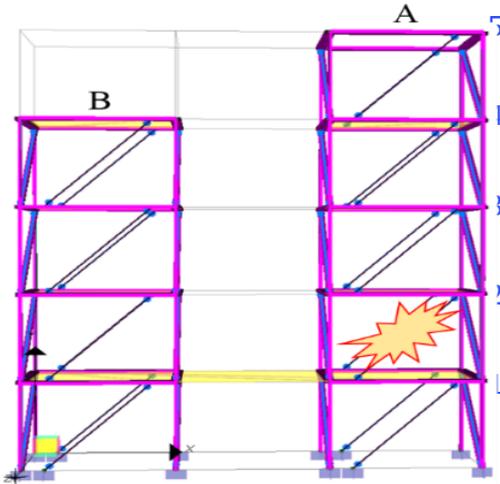
EQ600

EQ750



# Damage detection & Localization : Sammon Map

Damage Scenario 2



Reference

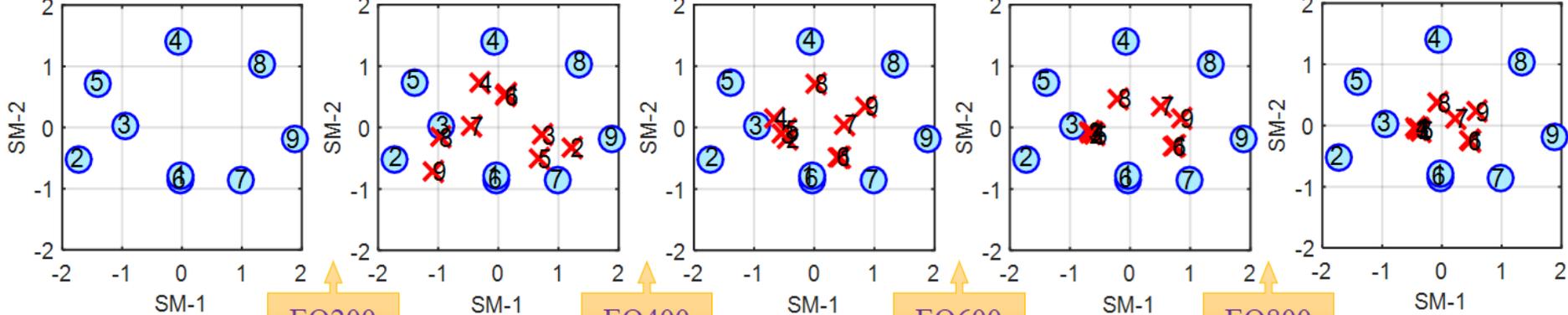
DS2, WN50-1

DS2, WN50-2

DS2, WN50-3

DS2, WN50-4

DS2, WN50-5



EQ200

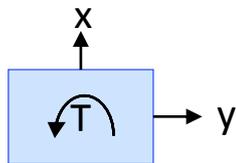
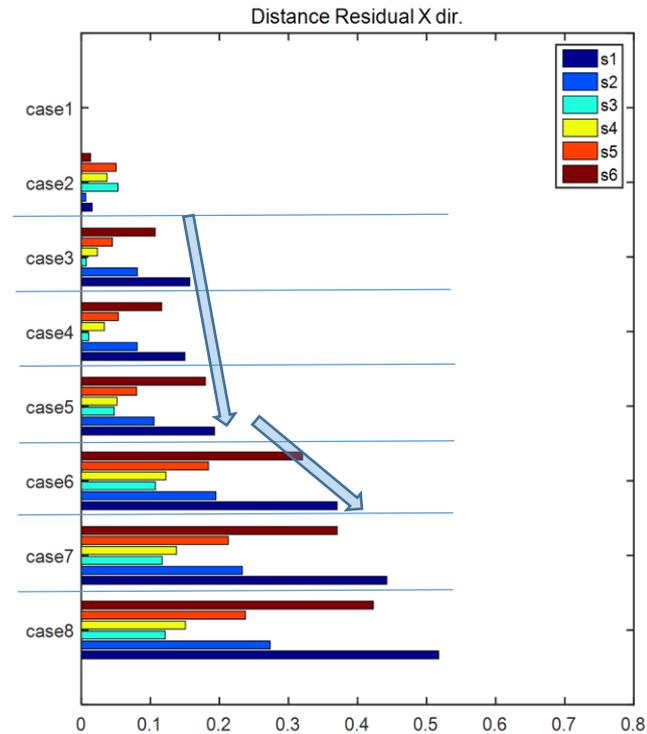
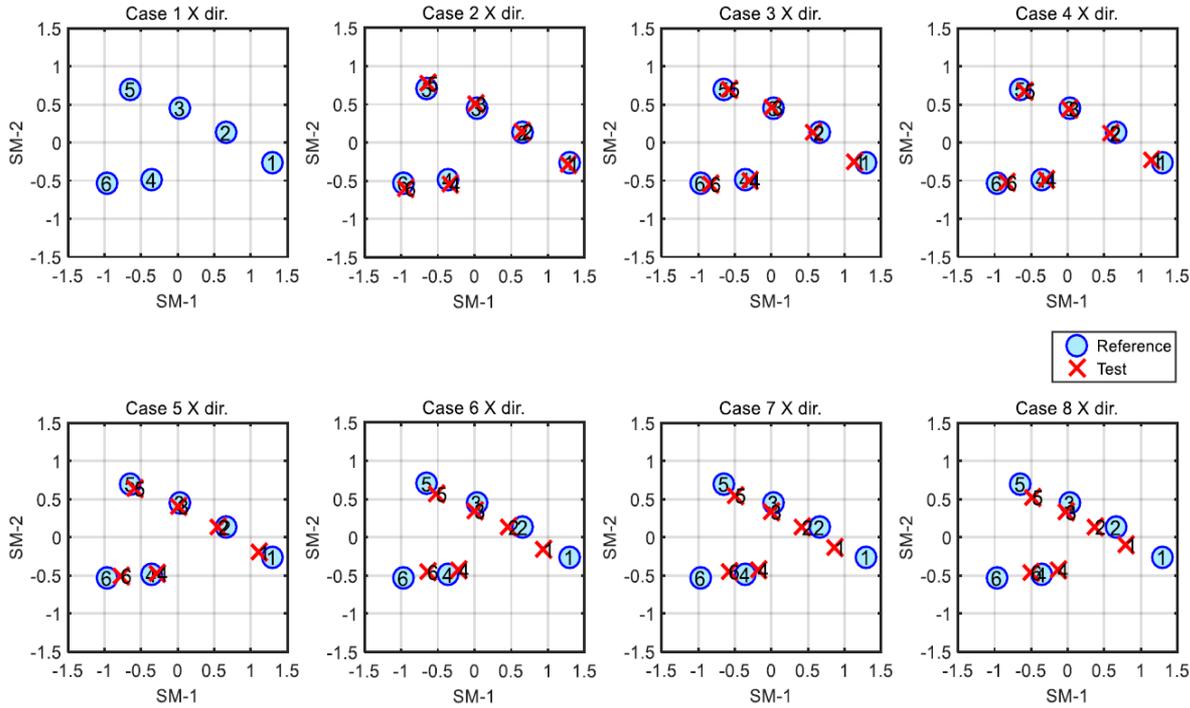
EQ400

EQ600

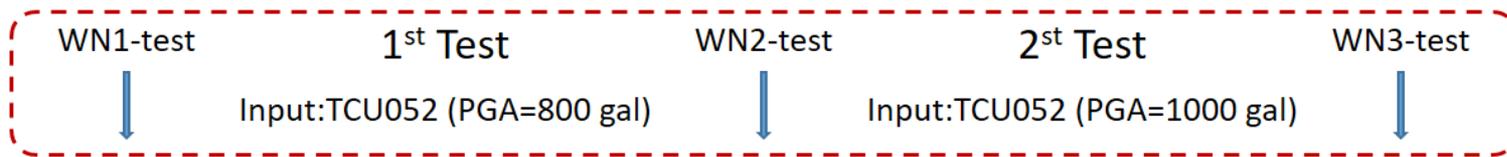
EQ800



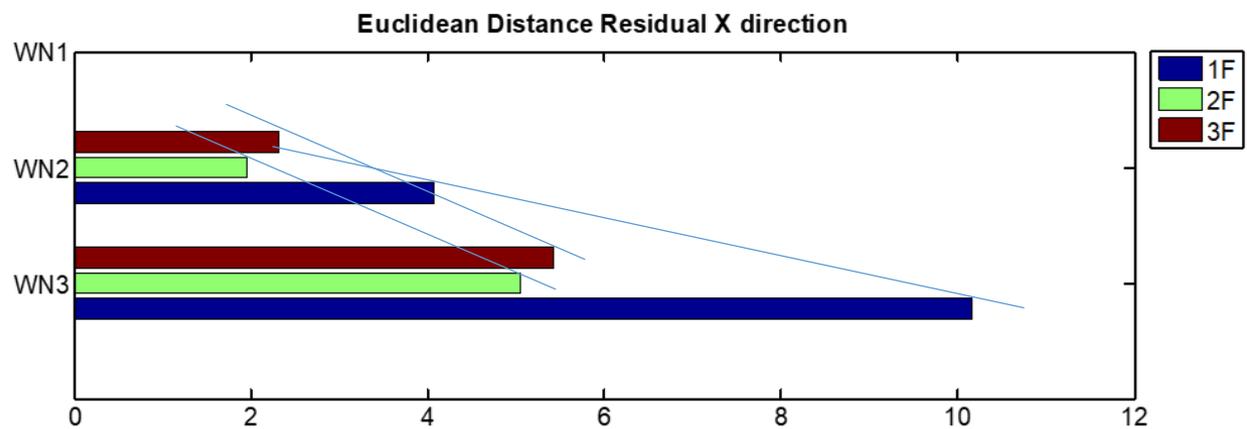
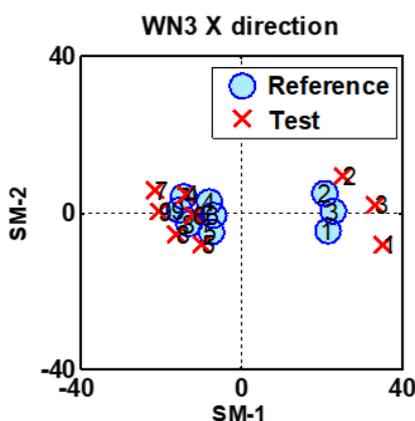
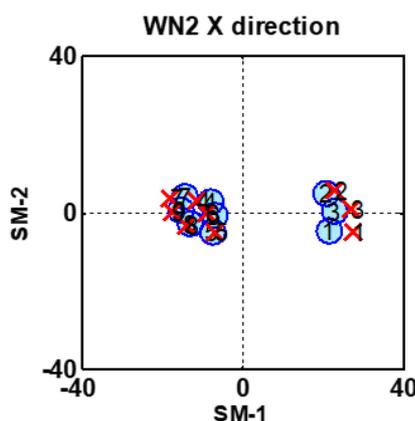
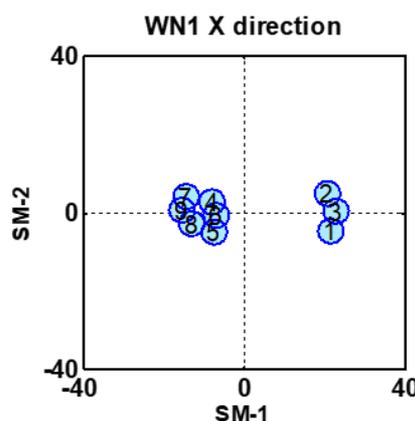
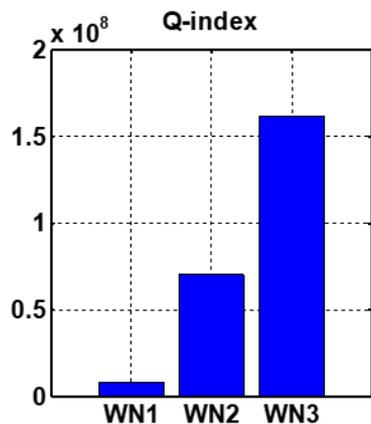
# Damage detection & Localization : Sammon Map



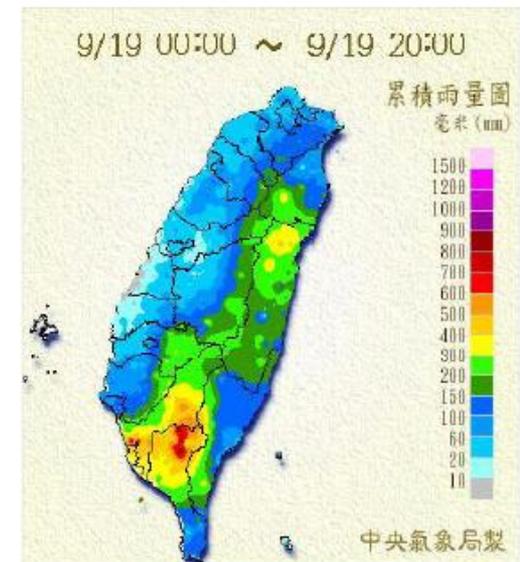
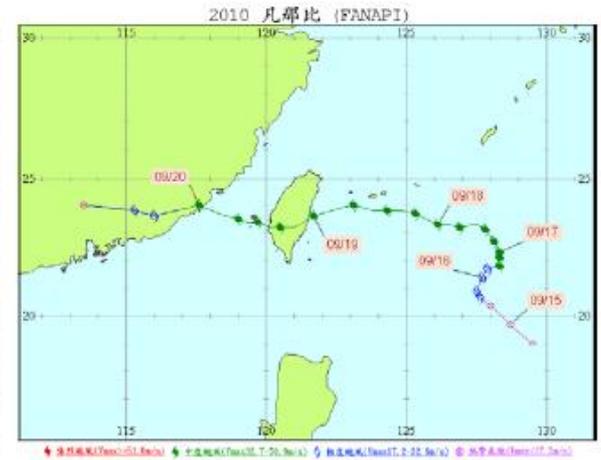
# NCREE-South Center Grand Opening Ambient Vibration Test



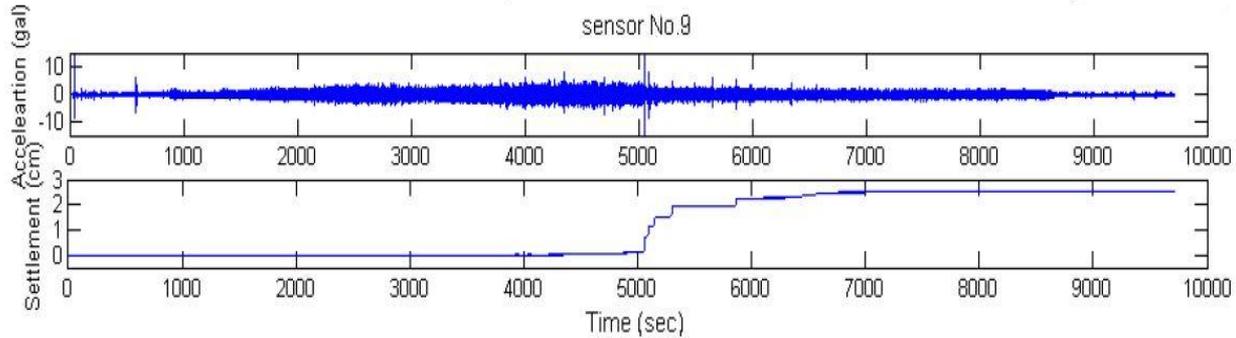
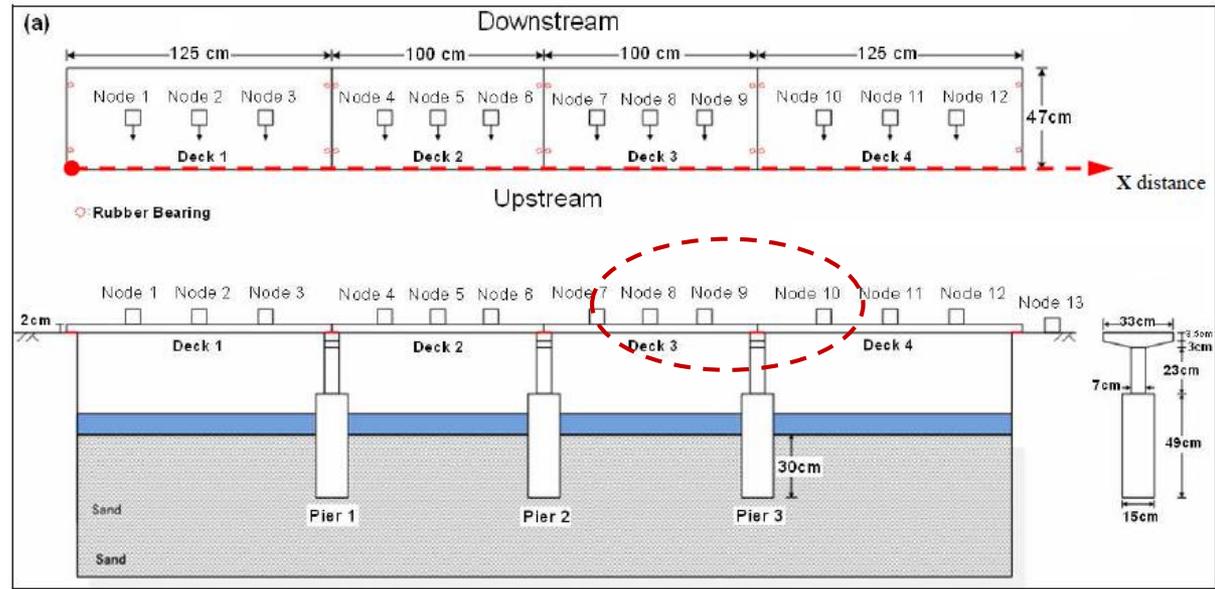
WN - Sammon map



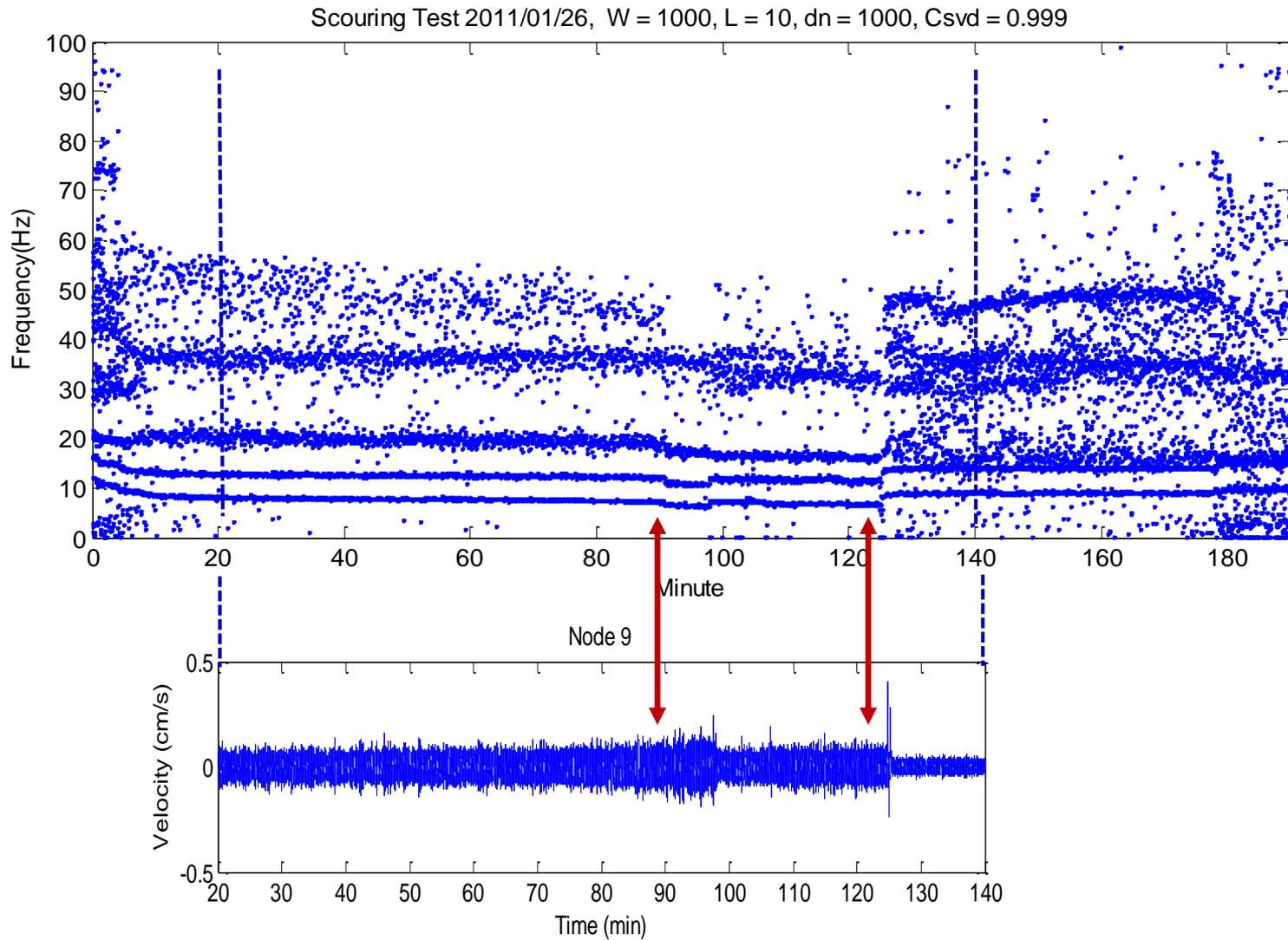
# Damage Assessment of Bridge Under Scouring Process



# Damage Assessment of Bridge Under Scouring Process



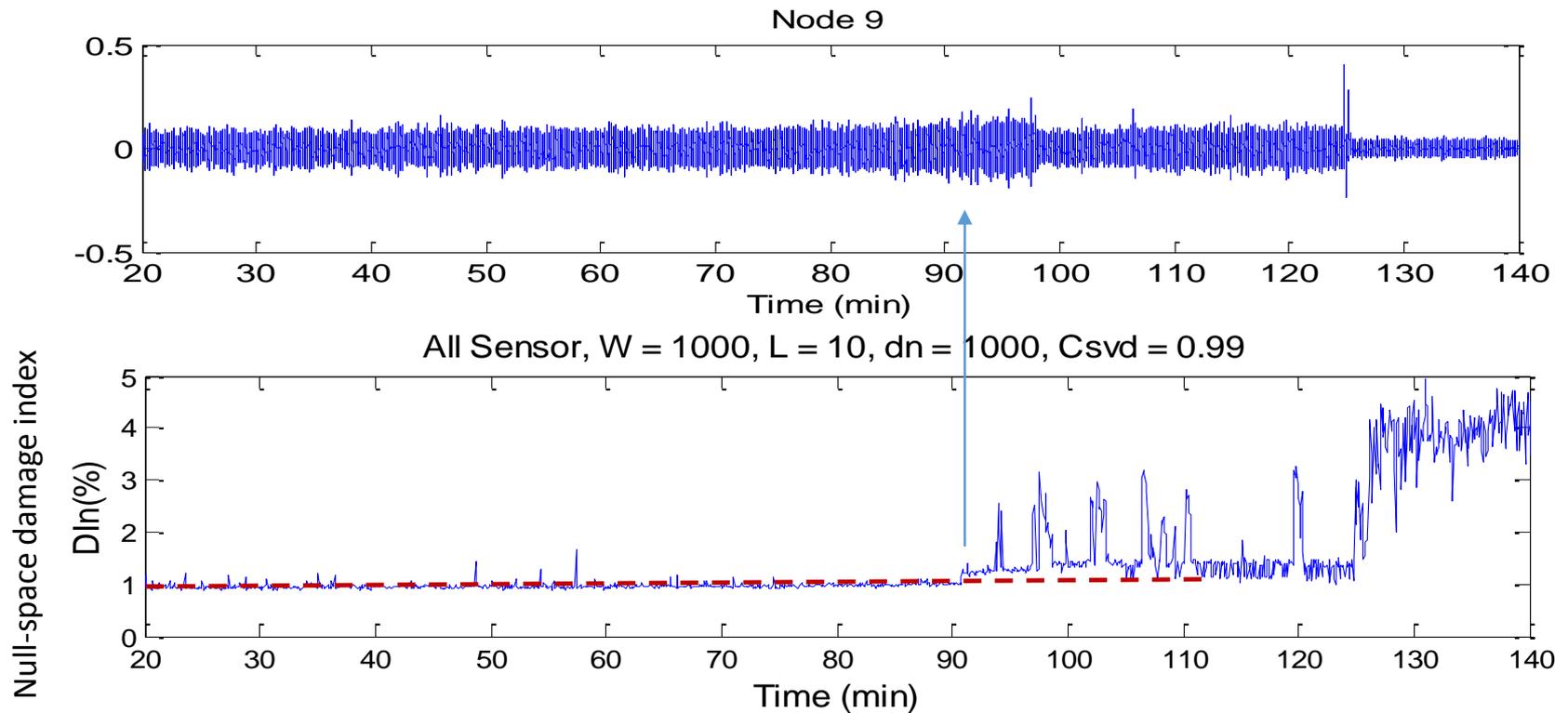
# Moving window SSI-COV (using velocity data)



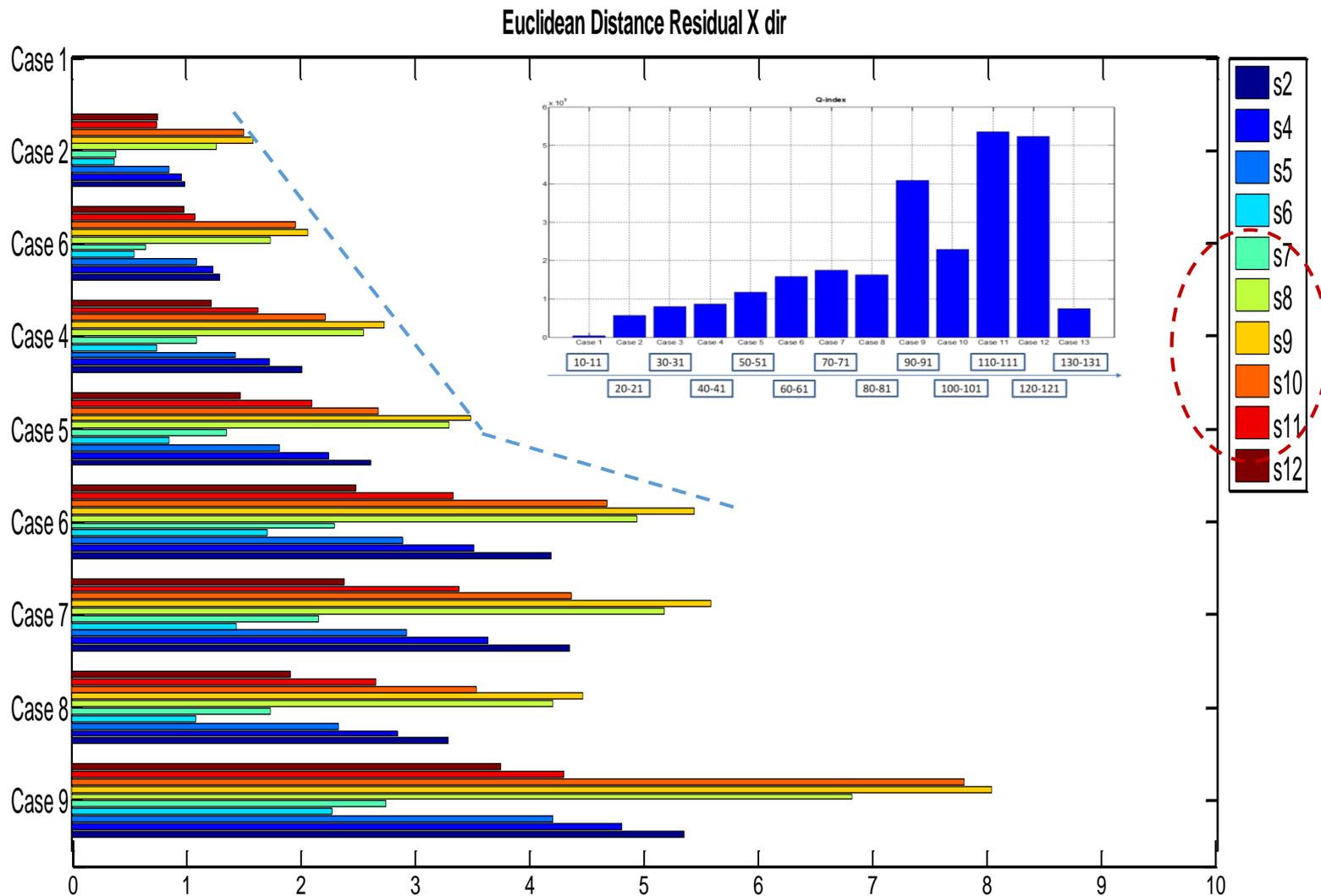
# Damage Detection Algorithms: Results from $DI_N$ & $DI_S$ (scouring test)



$$DI_n = \text{mean}\{|\mathbf{U}_{n0}^T \mathbf{U}_s|\}$$

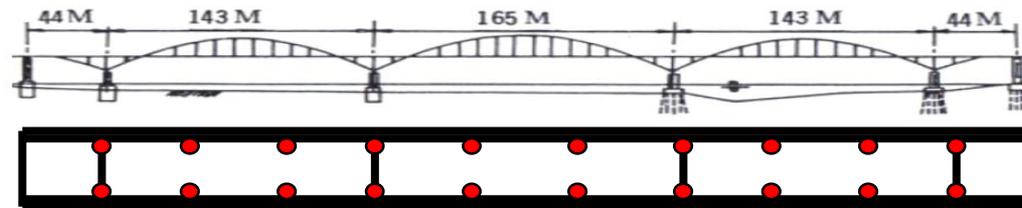


# Damage detection & Localization : Sammon Map (scouring test)



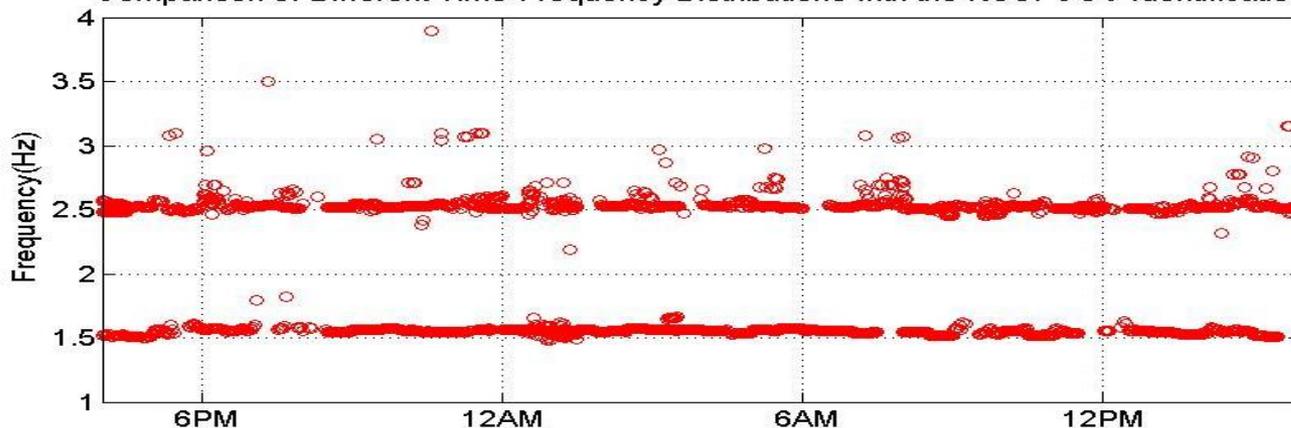
# Bridge Vibration Monitoring under Operating Condition

## Environmental Effects for Vibration-based SHM



2011/04/01-2011/04/02, PM14:00-PM14:00

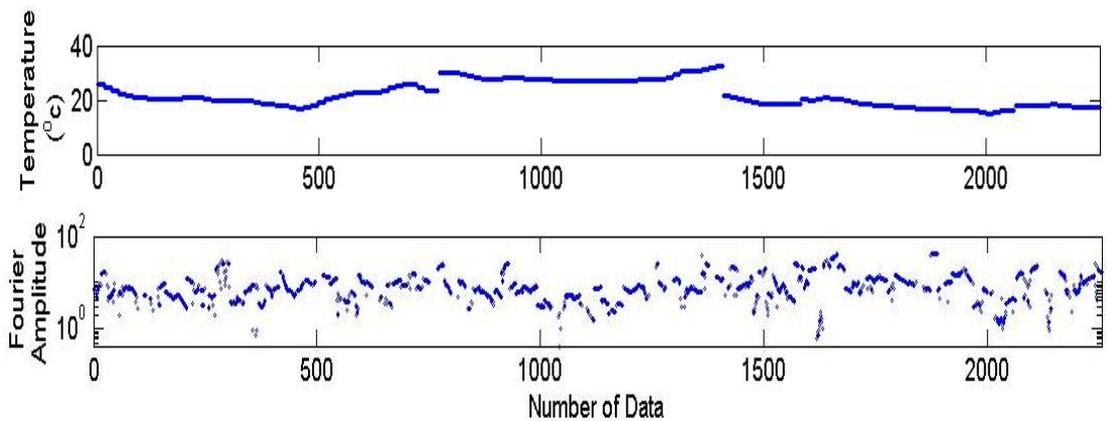
Comparison of Different Time-Frequency Distributions with the RSSI-COV Identification



Using moving window  
SSI-VOV algorithm

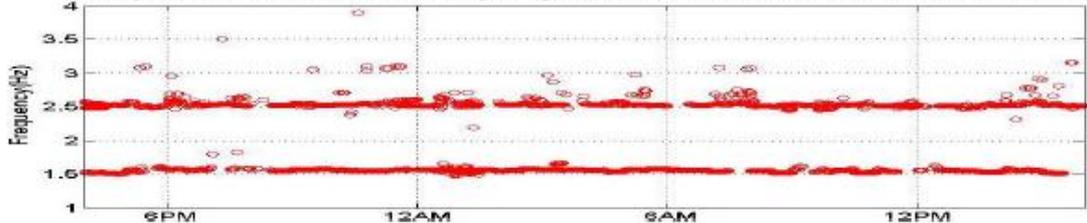


# Environmental Effect on Modal Parameter Identification

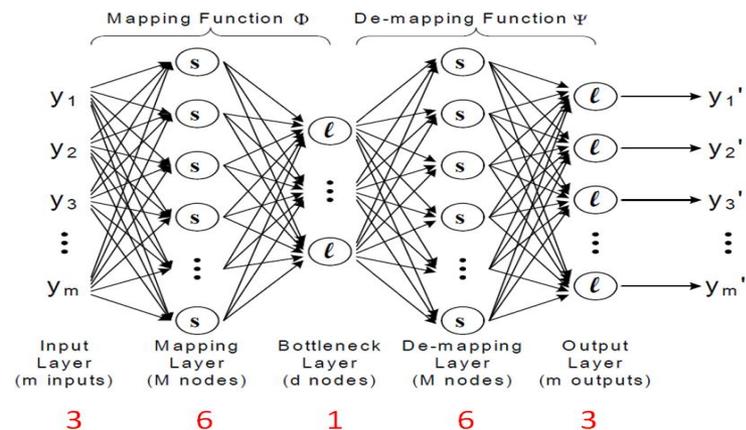
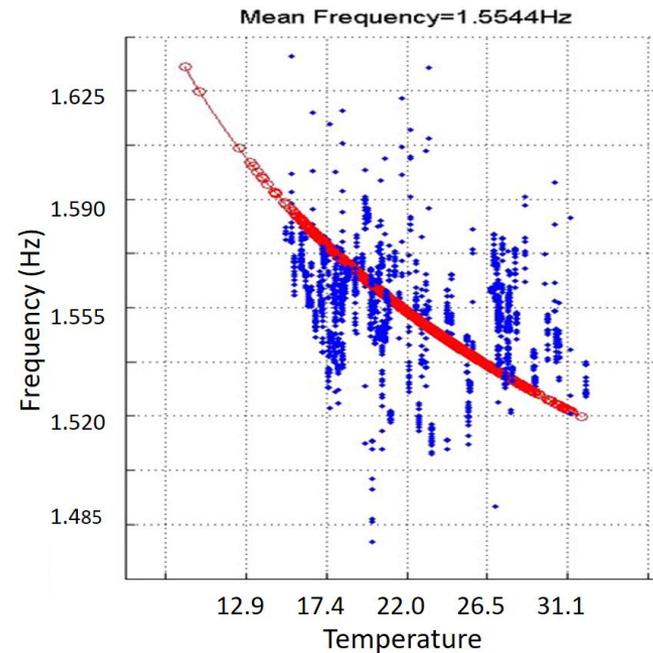
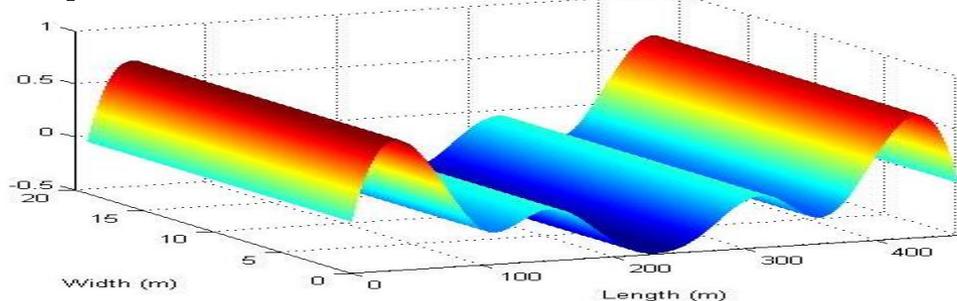


2011/04/01-2011/04/02, PM14:00-PM14:00

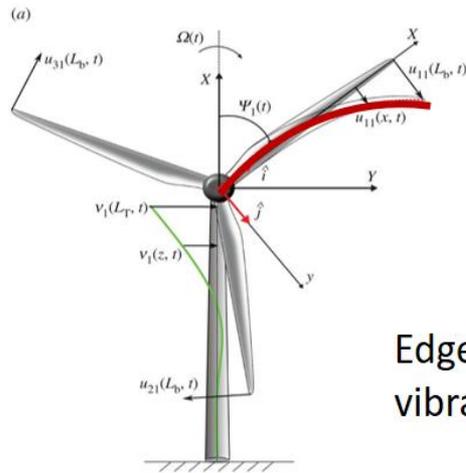
Comparison of Different Time-Frequency Distributions with the RSSI-COV Identification



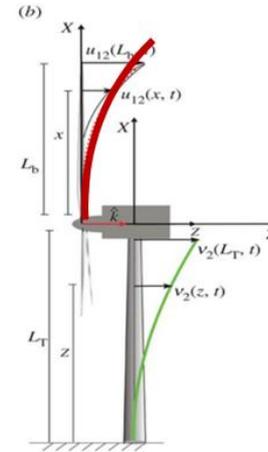
$f_1 = 1.554 \text{ Hz}$



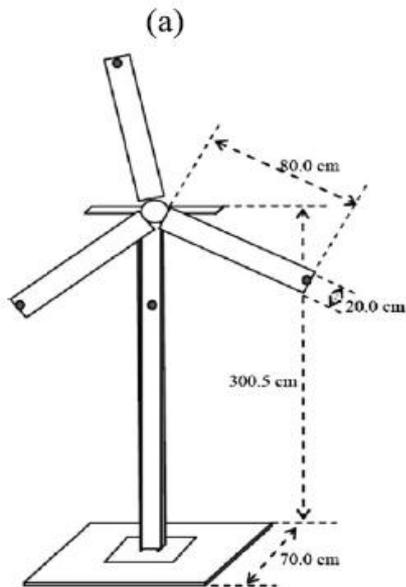
# System identification of wind turbine blade under operating condition



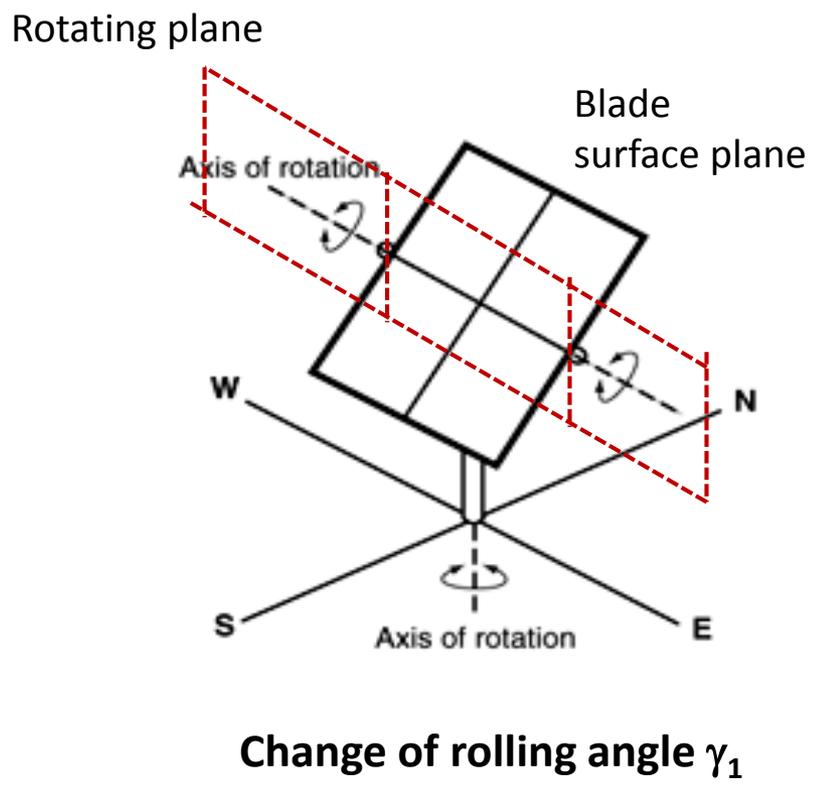
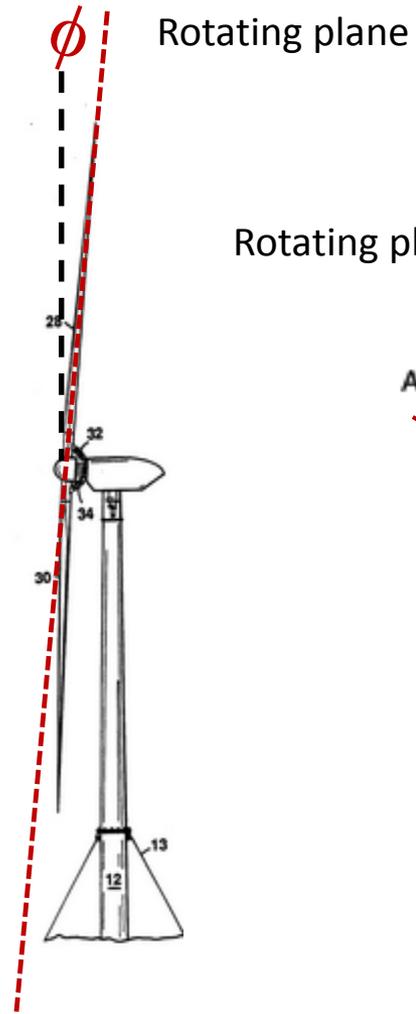
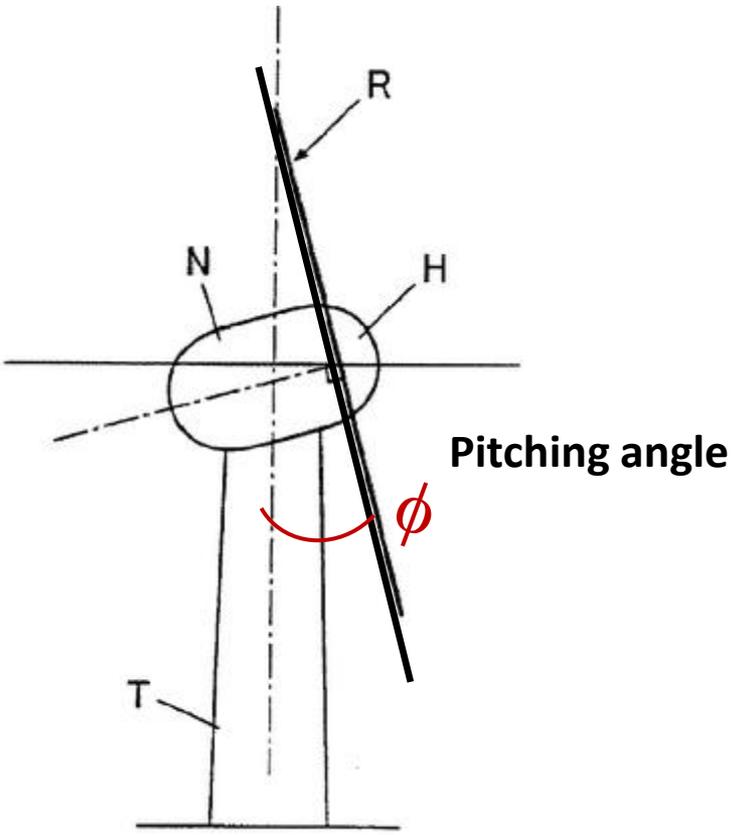
Edge-wise vibration



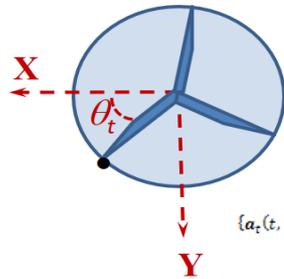
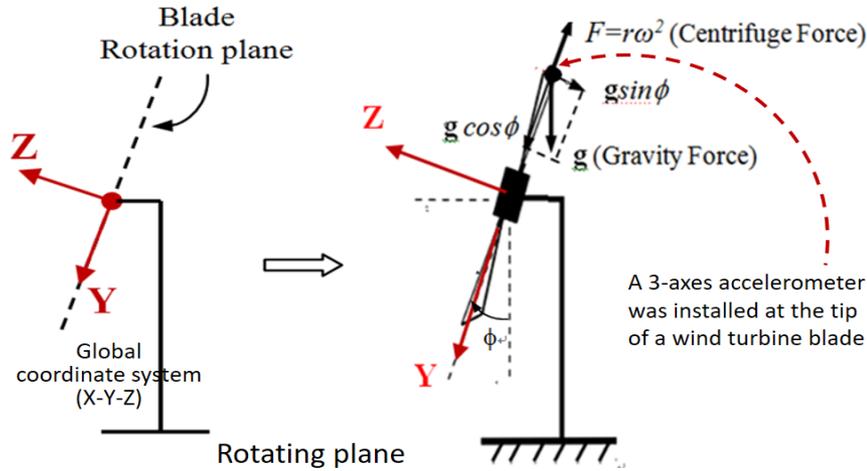
Flap-wise vibration



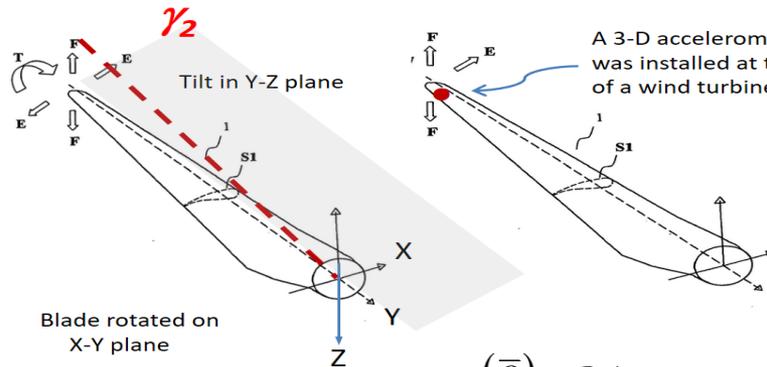
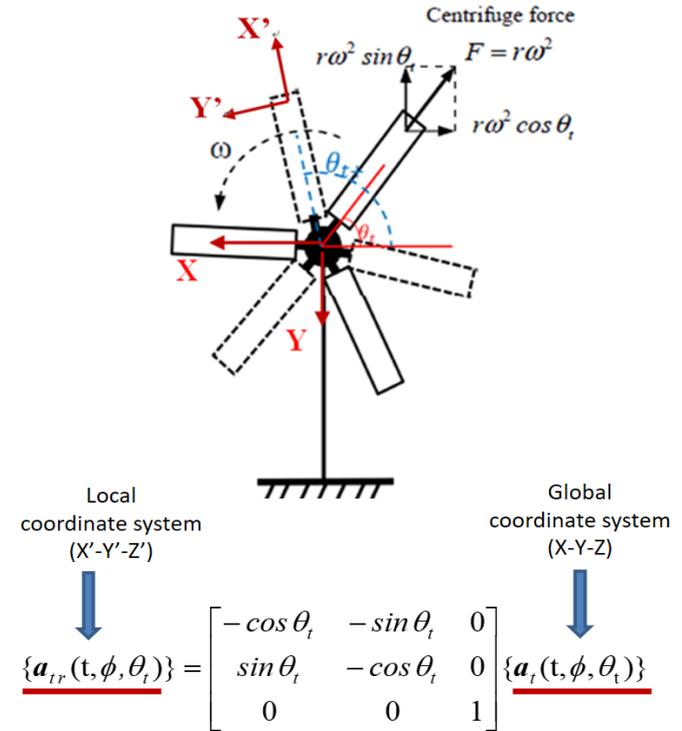
# Geometry setup of turbine blade



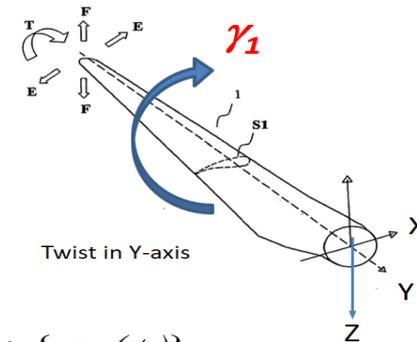
# Coordinate transformation between local and global coordinate system



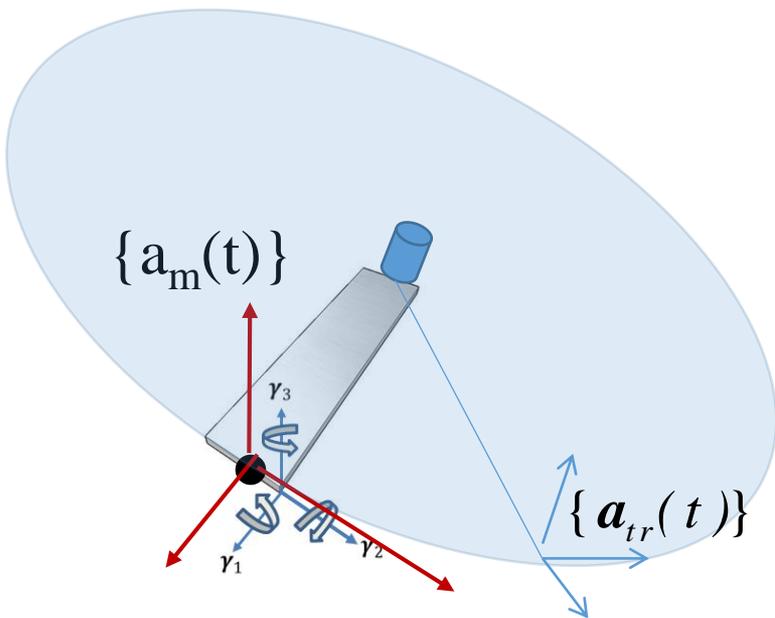
$$\{a_t(t, \phi, \theta_t)\} = \begin{bmatrix} a_{tx} \\ a_{ty} \\ a_{tz} \end{bmatrix} = \begin{bmatrix} -r\omega^2 \cos\theta_t \\ -r\omega^2 \sin\theta_t \\ 0 \end{bmatrix} + \begin{bmatrix} 1 & 0 & 0 \\ 0 & \sin\phi & \cos\phi \\ 0 & \cos\phi & -\sin\phi \end{bmatrix} \begin{bmatrix} 0 \\ 0 \\ g \end{bmatrix}$$



$$a_m(\bar{\beta}) = \mathcal{R}(-\gamma_{s1}, -\gamma_{s2}, -\gamma_{s3}) \{a_{tr}(t)\}$$



# Methodology of tracking blade geometry setup



$$\mathbf{a}_m(\bar{\boldsymbol{\beta}}) = \mathcal{R}(-\gamma_{s1}, -\gamma_{s2}, -\gamma_{s3}) \{ \mathbf{a}_{tr}(t) \}$$



Sensor  
coordinate system  
(X''-Y''-Z'')



Local  
coordinate system  
(X'-Y'-Z')

$$\mathcal{R} = \begin{bmatrix} \cos\theta + n_1^2(1 - \cos\theta) & n_1 n_2(1 - \cos\theta) - n_3 \sin\theta & n_1 n_3(1 - \cos\theta) + n_2 \sin\theta \\ n_1 n_2(1 - \cos\theta) + n_3 \sin\theta & \cos\theta + n_2^2(1 - \cos\theta) & n_2 n_3(1 - \cos\theta) - n_1 \sin\theta \\ n_3 n_1(1 - \cos\theta) - n_2 \sin\theta & n_3 n_2(1 - \cos\theta) + n_1 \sin\theta & \cos\theta + n_3^2(1 - \cos\theta) \end{bmatrix}$$

$$\mathbf{a}_m(\bar{\boldsymbol{\beta}}) = \mathcal{R}(-\gamma_{s1}, -\gamma_{s2}, -\gamma_{s3}) \{ \mathbf{a}_{tr}(t) \}$$

Measurement

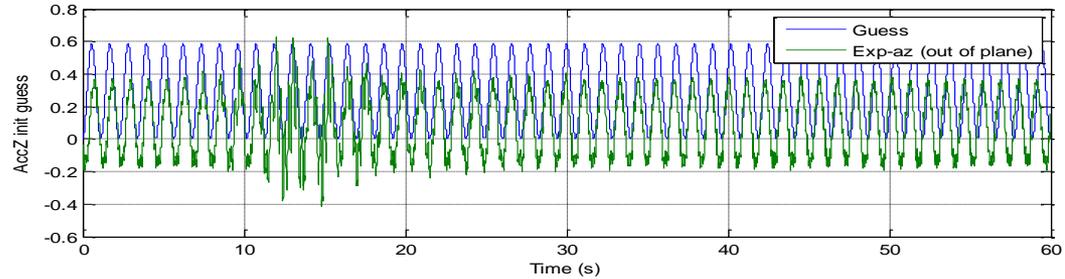
Minimization of  $J(\bar{\boldsymbol{\beta}}) = \left\| \mathbf{a}_e(t, \bar{\boldsymbol{\beta}}) - \mathbf{a}_m(t) \right\|$

Determine  $\bar{\boldsymbol{\beta}} = \langle \theta \ \gamma_{s1} \ \gamma_{s2} \ \gamma_{s3} \ \varphi \rangle$

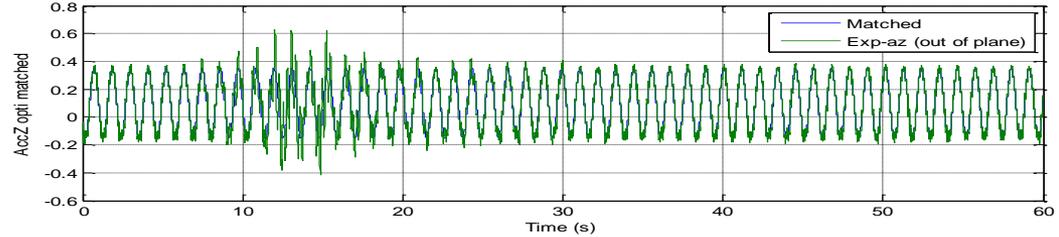


# Out-of-plane motion of turbine blade (test case of 50 rpm)

Recorded & initial assumption of flap-wise wave forms



Recorded and estimated flap-wise wave form



Residual signal of flap-wise wave form

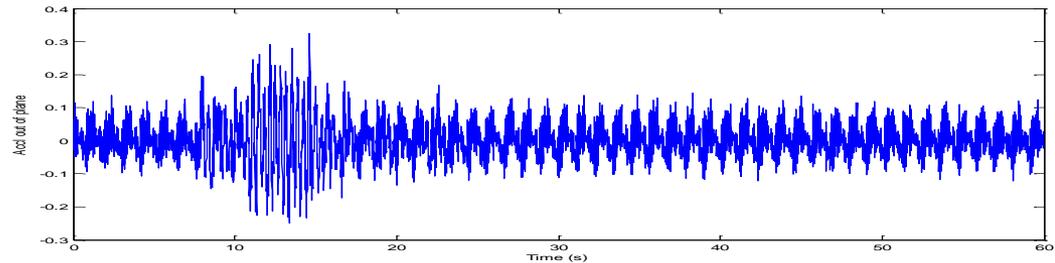
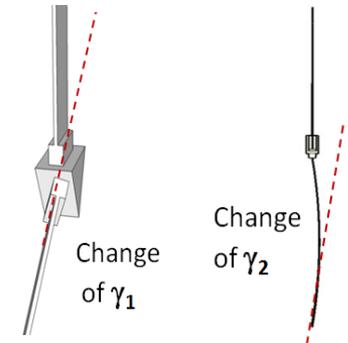


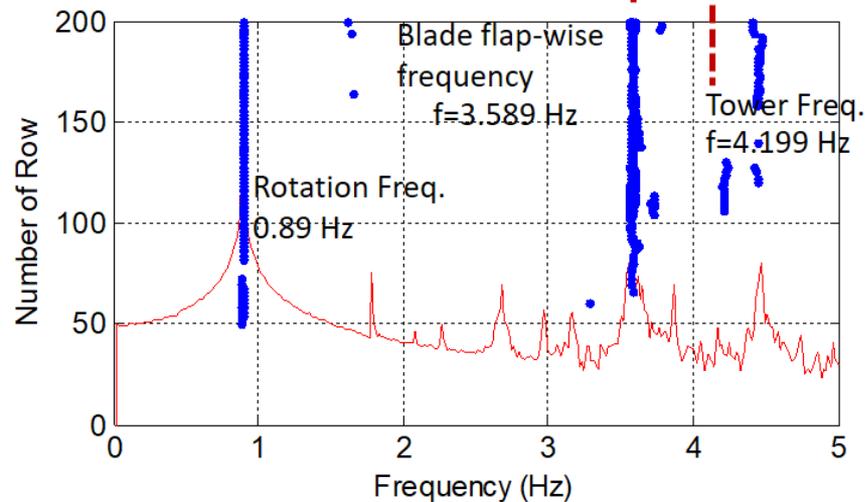
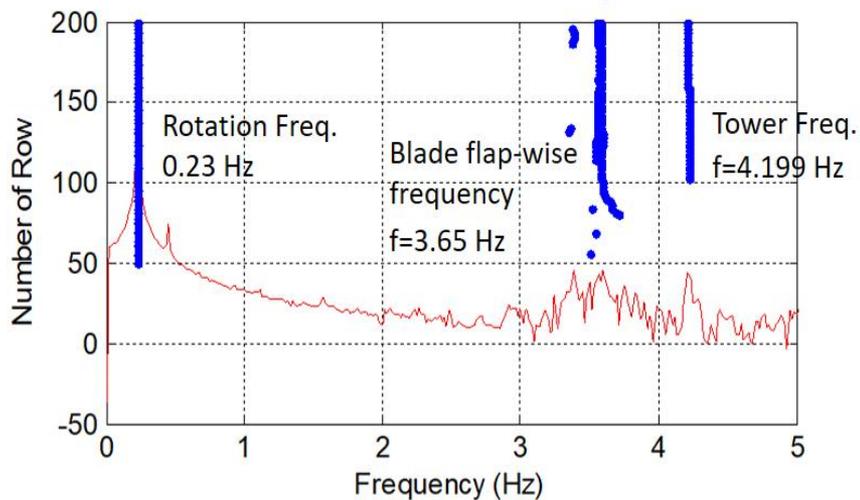
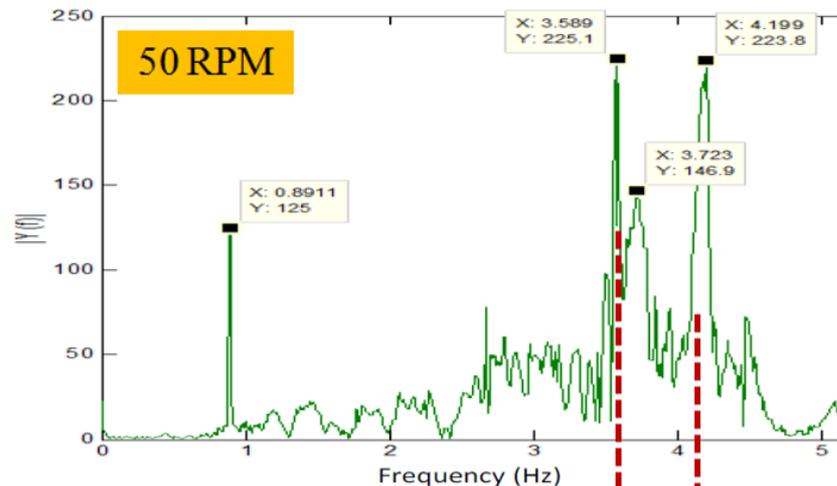
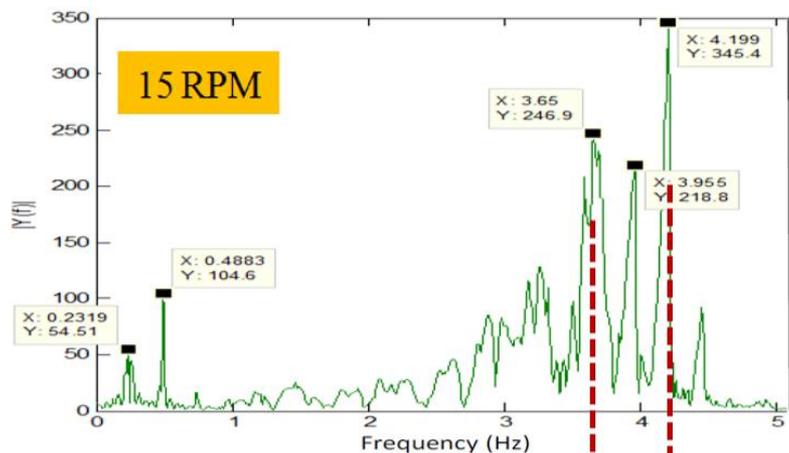
Table 1b: Identified wind turbine pitching and rolling angles from Test-2.

Test-2	$\phi$	$\gamma_1$	$\gamma_2$	$\gamma_3$
15 rpm: Case 1	89.96 (90.0)	-6.58 (-5.0)	12.81 (10.0)	0.1 (0.0)
15 rpm: Case 2	90.18 (90.0)	-9.6 (-10.0)	12.05 (10.0)	0.63 (0.0)
15 rpm: Case 3	85.1 (90.0)	85.1 (90.0)	10.69 (10.0)	-0.84 (0.0)

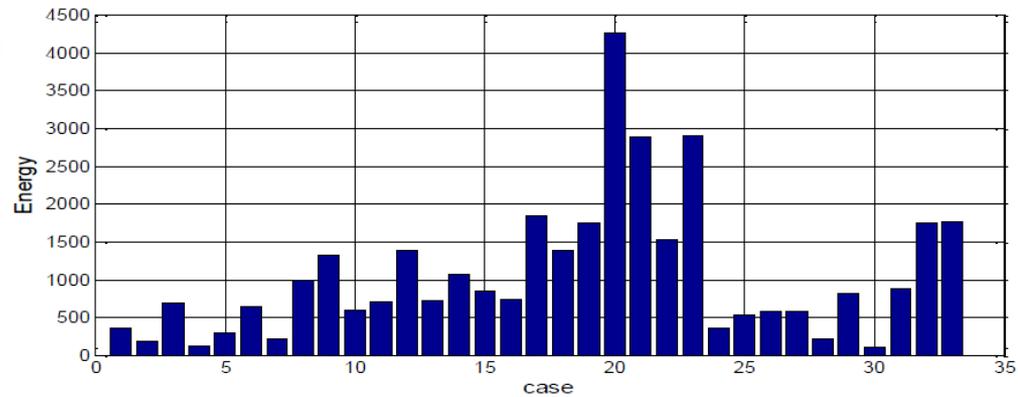
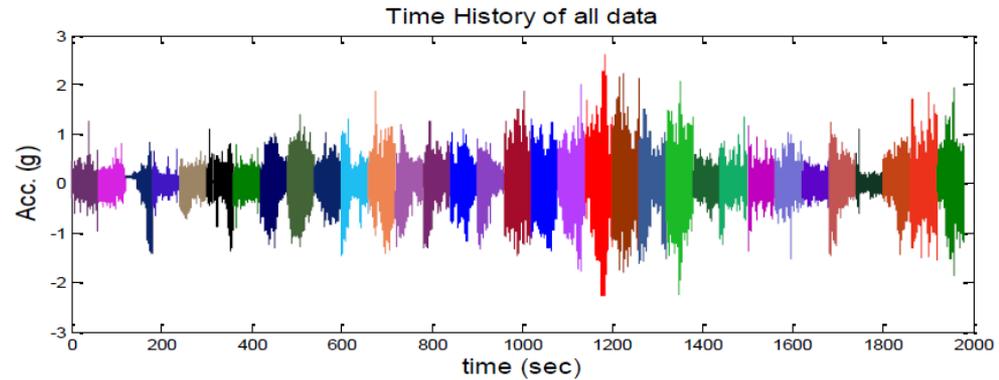
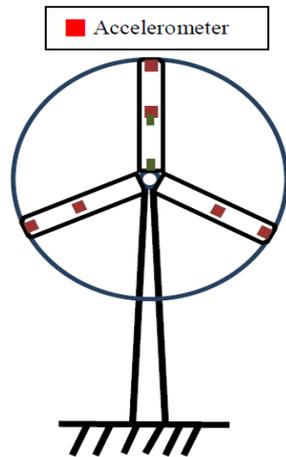
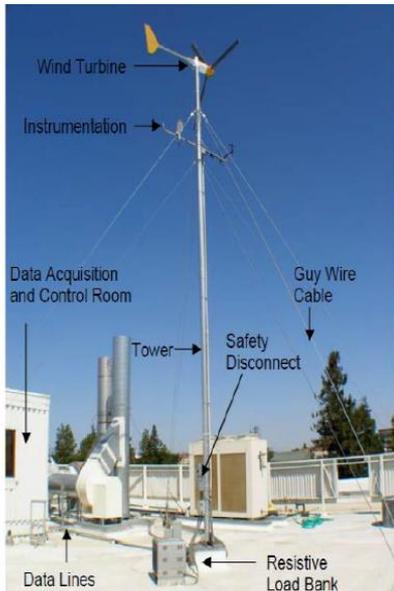
Note: (\*) indicate the blade rolling angle in its original setup.



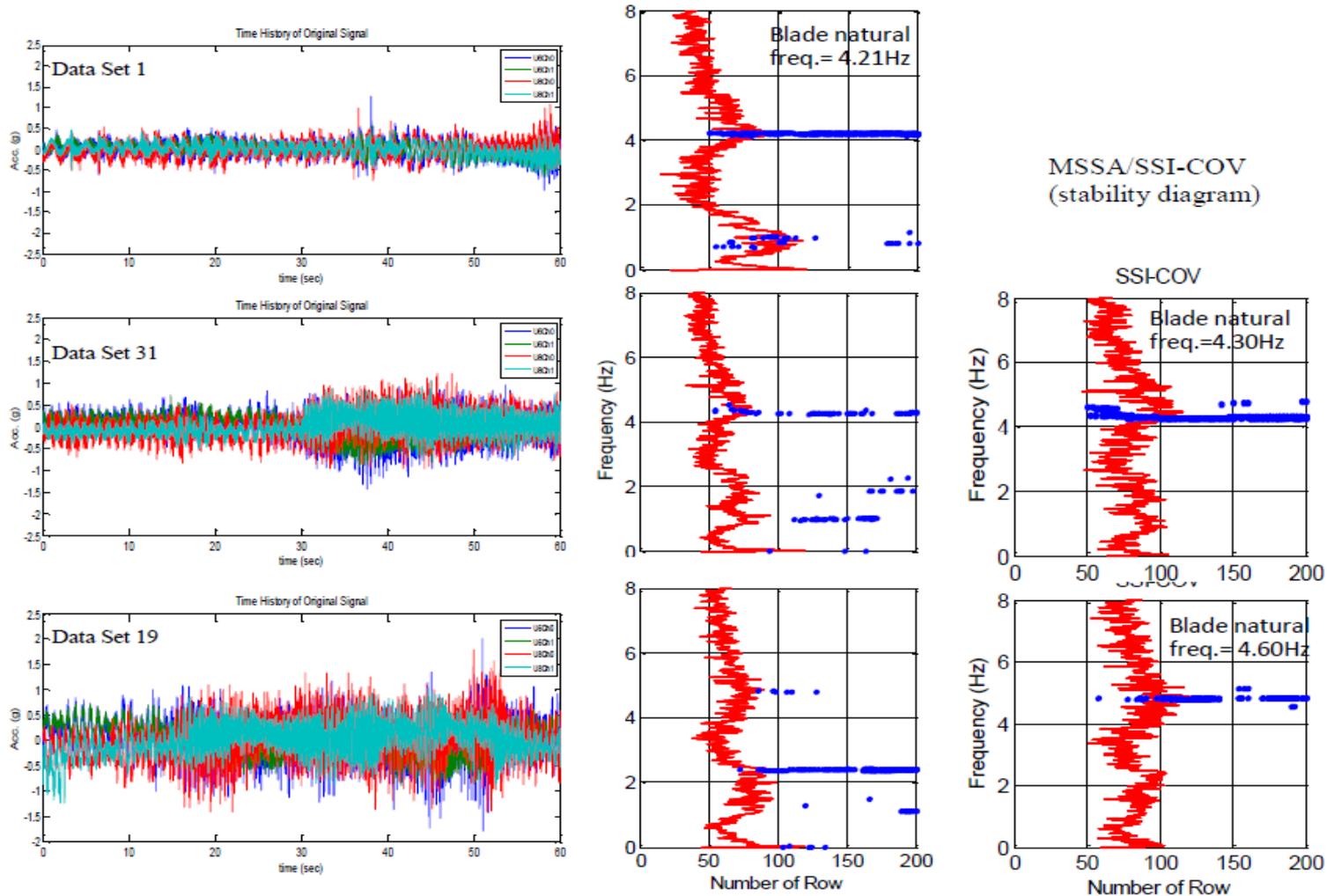
# Results of Identification (1)



# Field Experimental Study



# Field Experimental Study

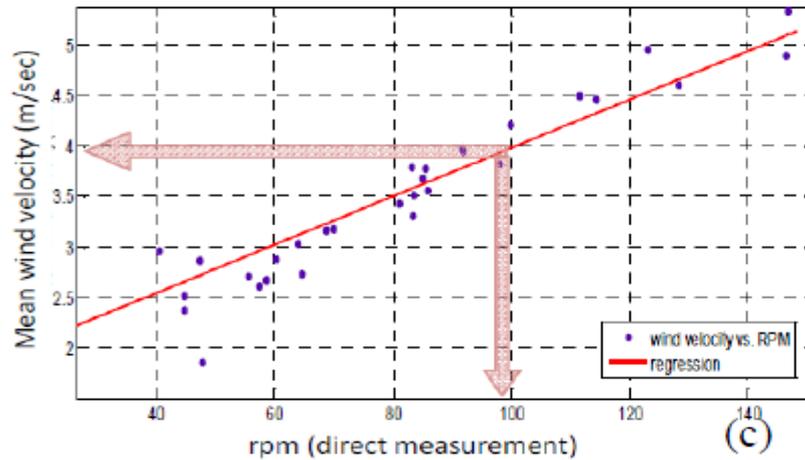


(a) Recorded acceleration of out-of-plane motion of blade from three different dataset  
 (b) Plot the stability diagram (from SSI-COV) from each dataset, (c) Plot the stability diagram (using MSSA to remove the rotation frequency signal) for dataset 31 and 19.

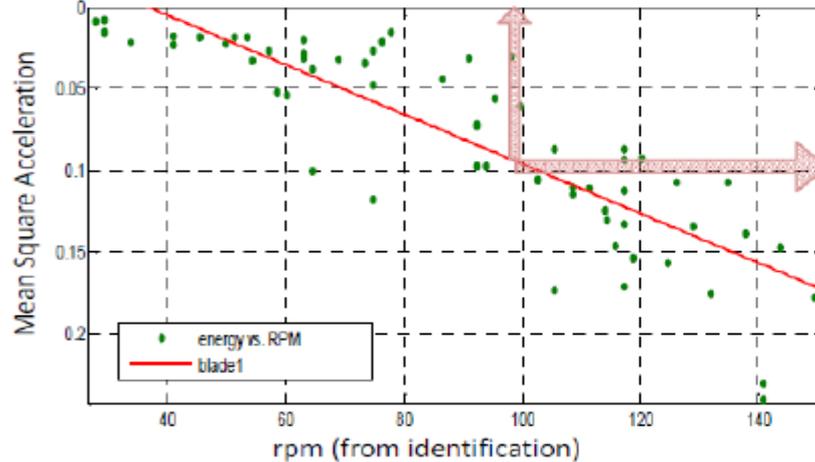


# Field Experimental Study

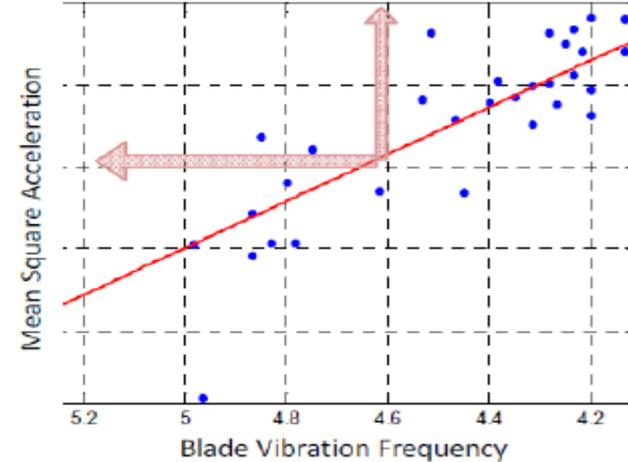
(a)



(b)



(c)



(a) The relationship between the mean wind velocity, the turbine rotation Frequency and the identified blade vibration frequency.



# Conclusions

## Centralized Data Analysis Techniques

System Identification :

Stochastic Subspace Identification (**ambient data**)

Recursive Subspace Identification (**earthquake response**)

Damage Assessment Level-3 :

LSSM+EMCM (stiffness reduction---earthquake response)

Damage Detection & Localization (Level-1 & Level-2):

Null-space damage index

Sammon map--- 2D visualization

Almost  
Real-time  
Damage  
Assessment

## Sensor-Level Data Analysis Techniques

Damage Detection & Localization (Level-1 & Level-2):

Wavelet-based correlation analysis



# Challenges in SHM of Civil Structures

**Civil  
Infrastructures**



- Huge size (large scale) and vast mass of materials,
- Long service life (> 50 years),
- Harsh and varying environmental conditions
- In-place conditions different from the design assumptions



***OMA based  
damage assessment***

- ✓ Develop measurement strategies,
- ✓ Increase the number of excited modes,
- ✓ Eliminate environmental influences,
- ✓ Increase the sensitivity to local damages,



***Damage detection  
(alarm level)***

- ✓ Explore more damage related dynamic features,
- ✓ Consider statistically relevant deviation,
- ✓ For permanent monitoring '**automatic system identification**' is mandatory,
- ✓ Highly advisable for periodic monitoring,
- ✓ Develop modal updating technologies (Optimization algorithm)



2017	Jun-Da Chen & <b>Chin-Hsiung Loh</b> , "Tracking Modal Parameters of Building Structures from Experimental Studies and Earthquake Response Measurements," <i>Published in Int. J. of Structural Health Monitoring</i> , March 2017 DOI: 10.1177/1475921717696339.
2017	<b>Chin-Hsiung Loh</b> & Jun-Da Chen, "Tracking Modal Parameters from Building Seismic Response Data Using Recursive Subspace Identification Algorithm," <i>Published in Int. J. Earthquake Engineering &amp; Structural Dynamics</i> , April 2017, DOI: 10.1002/eqe.2900
2016	<b>Chin-Hsiung Loh*</b> , Chuan-Kai Chan, Sheng-Fu Chen, Shieh-Kung Huang, "Vibration-based Damage Assessment of Steel Structure Using Global and Local Response Measurements," <i>Earthquake engineering &amp; Structural dynamics</i> , 2016; 45:699-718.
2015	<b>Chin-Hsiung Loh*</b> , Yu-Ting Huang, Wan-Ying Hsiung, Yuan-Sen Yang, Kenneth J. Loh, "Vibration-Based Identification of Rotating Blades Using Rodrigues' Rotation Formula from A 3-D Measurement," <i>Journal of Wind and Structures</i> , Vol.21, No.6, December 2015, pp.677-691.
2015	Chin-Hsiung Loh*, Shu-Hsien Chao, Jian-Huang Weng, Tzu-Hsiu Wu, "Application of Subspace Identification Technique to Long-Term Seismic Response Monitoring of Structure," <i>Earthquake Engineering &amp; Structural Dynamics</i> , (2015), 44:385-402
2015	<b>Chin-Hsiung Loh</b> , T Y Hung, S F Chen and W T Hsu, "Damage Detection in Bridge Structure Using Vibration Data under Random Travelling Vehicle Loads," <i>Journal of Physics: Conference Series (DAMAS)</i> 628 (2015) 012044.
2014	Chao, S.H., and <b>Loh, Chin-Hsiung</b> , "Vibration-based damage identification of reinforced concrete member using optical sensor array data," <i>J. Structural Health Monitoring</i> , Vol.12, No. 5-6, 397-410. 2014. IF=3.193
2014	Chao, S.H., <b>Chin-Hsiung Loh</b> , Tseng, M.H., "Structural Damage Assessment Using Output-Only Measurement: Localization and Quantification," <i>Int. Journal of Intelligent Material Systems and Structures</i> , Vol. 25(9) 1097-1106, 2014. (IF=0.45)
2014	<b>Loh, Chin-Hsiung</b> . "Sensing solutions for assessing and monitoring of dams," Chapter 10, <i>Sensor Technologies for Civil Infrastructures (Vol.2: Applications in Structural Health Monitoring)</i> , Edited by M.L. Wang, J.P. Lynch and H. Sohn, Elsevier Ltd 2014, pp: 275~308. (Book Chapter Contribution) (IF=0.45)
2013	Chao, S.H., <b>Loh, C.H.</b> , Tseng, M.H., "Structural Damage Assessment Using Output-Only Measurement: Localization and Quantification," <i>Accept for publication in Int. Journal of Intelligent Material Systems and Structures</i> , June 2013. IF:1.523
2013	Chao, S. H. and Loh, C. H., "Application of Singular Spectrum Analysis to Structural Monitoring and Damage Diagnosis of Bridges," <i>J. of Structures and Infrastructural Systems</i> 2) Volume 10, 2014 - <u>Issue 6</u> 708-727
2013	<b>Loh, C.H.</b> and Liu, Y.C., "Application of recursive SSA as data pre-processing filter for stochastic subspace identification," <i>Accept for publication in Smart Structures and Systems</i> , Vol.11, No.1 (2013) IF:1.430



# Acknowledgements

## 科技部專題研究案

**2016-8/2017-7:** MOST 105-2625-M-002-003; MOST 105-2221-E-002-026  
**2015-8/2016-7:** MOST 104-2625-M-002-016; MOST 104-2221-E-002-013  
**2014-8/2015-7:** MOST103-2625-M -002-006; MOST 103-2221-E-002-064

## Research Assistant from Prof. Loh's research Lab



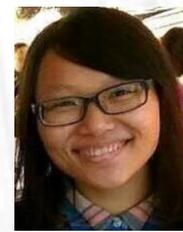
林佳樺



薛汶



陳俊達



涂雅靜



李宗憲



許維庭



黃昱廷



熊婉贏



葉乃睿



**Than you for your listening !**

*Questions ?*



臺灣大學



National Taiwan University