OpenFOAM for AI CFD

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Motivations

▣ Numerical simulations of CFD & CSD become more powerful (in accuracy, speed, memory,..), 그렇지만, practical application 등의 수치해석의 정확도는 높아지고 있으나 실시간 계산과 Digital Twin 으로의 응용은 제한이 많음.

▣ *<u>실시간 계산/예측, 설계,</u> 디지털 트윈에* 사용되어지기 위해서는 적은 수의 관심 성능 변수 (항력, 추력, 양력)에 대한 surrogate model을 사용하는 기법은 기존에도 많았음: Kriging, radial basis function, artificial neural network. Scalar outputs: 공력, 항력, 추력; Field of state variables (p, , velocities, …)

▣ **실시간으로 CFD와 같은 O($10^{5\sim6}$)차수의 상태변수를 구할 수는 없을까?**

→ ROM using <u>POD-Machine Learning</u>

→ AI methods for pattern/image process, prediciton & design: CNN, LSTM, GAN

❑ <u>Input parameter가</u> 다양할 수 있을까? 유동조건 (Re, Mach, AOA), 형상, 시간 등

▣ 차수저감 모델과 인공지능 기법 등의 다양한 데이터 기반 모델과 기법들이 사용되어질 수 있다. <u>인공지능기법이 최선인가?</u>

Contents

I. POD-based Reduced Order Model

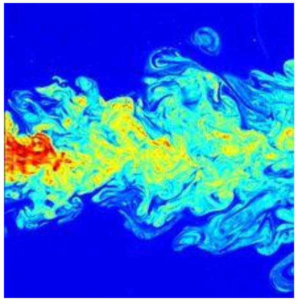
- **Dimensionality reduction shape and time**
- **POD-GPR (Shape) vs. POD-LSTM (Time)**

II. Deep neural network (DNN) based Reduced Order Model

- **Convolutional Neural Network – U Net**
- Time, Flow conditions (Mach or AOA), and Shape
- Generative Adversarial Network for Design

Reduced Order Model

- Many scientific problems are of high dimensions in the complexity with coherent structures of various scales; i.e., turbulent flows, wing trailing vortex, storms, etc.



(source: Turbulence, Wikipedia)

(source: No Matter What You Fly, This Wake Turbulence Accident Could Happen To You, Boldmethod)

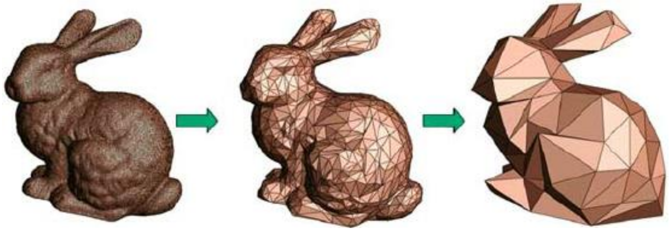
(source: "Don't play games with it": Hurricane Florence, weakens slightly, as it churns toward East Coast, CBS)

- **Reduced Order Model(ROM)**

• Dynamic behavior of complex and nonlinear physical systems

• Full order model **decomposed** into **a sum of linear basis functions or modes: (**When taking 100 snapshots to the 86214 grid points, only calculation of 100 by 100 matrices are needed.)

Stanford Bunny



- Proper Orthogonal Decomposition Methods
- Reduced Basis Methods
- Balancing Methods
- Simplified Physics or Operational based Reduction Methods

Proper Orthogonal Decomposition(POD) Method

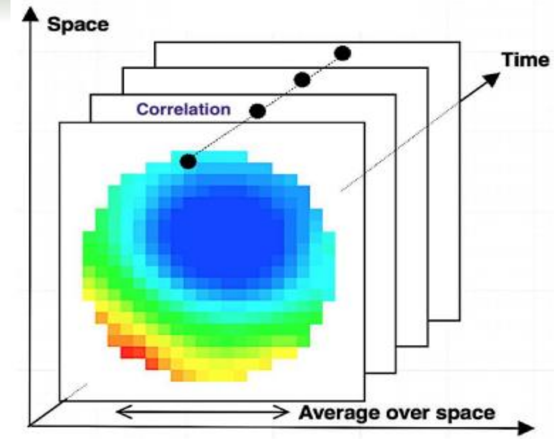
- **Fredholm integral equation (Eigenvalue equation)**

$$\int R(x,x')\phi(x')dx' = \lambda\phi(x)$$

- **Description of Eigenfunction** $\phi(x)$

$$\phi(x) = \sum_{n=1}^{M} q_n u^{(n)}(x) \qquad u^{(n)}(x) = u(x,t_n)$$

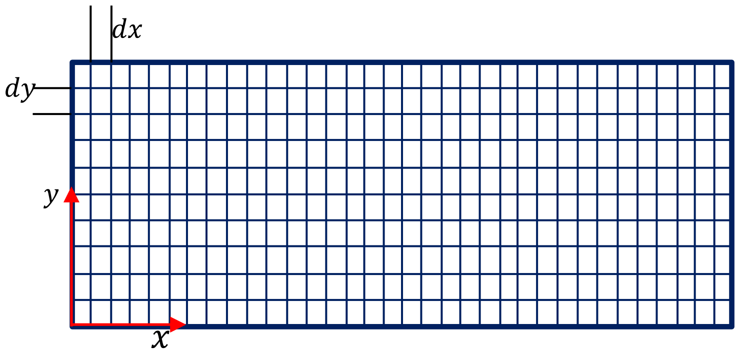
Eigenvector of R



t_n Sampling time

M No. of snapshots

- **2–dimensional space**



$$\begin{bmatrix} [a_{11}] & [a_{12}] & \cdots & [a_{1N}] \\ [a_{21}] & [a_{22}] & \cdots & [a_{2N}] \\ \vdots & \vdots & \ddots & \vdots \\ [a_{N1}] & [a_{N2}] & \cdots & [a_{NN}] \end{bmatrix} \begin{bmatrix} \phi_1 \\ \phi_2 \\ \vdots \\ \phi_N \end{bmatrix} = \lambda \begin{bmatrix} \phi_1 \\ \phi_2 \\ \vdots \\ \phi_N \end{bmatrix}$$

$$[a_{ij}] = dxdy \begin{bmatrix} \langle u_i u_j \rangle & \langle u_i v_j \rangle \\ \langle v_i u_j \rangle & \langle v_i v_j \rangle \end{bmatrix}$$

Ref) Sirovich, L. (1987). "TURBULENCE ANS THE DYNAMICS OF COHERENT STRUCTURES PART 1: COHERENT STRYCTYRES", *Quarterly of Applied Mathematics*, 45(3), 561-571.

Proper Orthogonal Decomposition(POD) Method

- **2-dimensional space**

$$dxdy\sum_{j=1}^{N}\begin{bmatrix}\frac{1}{M}\sum_{n=1}^{N}u_i{}^{(n)}u_j{}^{(n)} & \frac{1}{M}\sum_{n=1}^{N}u_i{}^{(n)}v_j{}^{(n)}\\ \frac{1}{M}\sum_{n=1}^{N}v_i{}^{(n)}u_j{}^{(n)} & \frac{1}{M}\sum_{n=1}^{N}v_i{}^{(n)}v_j{}^{(n)}\end{bmatrix}\sum_{l=1}^{M}q_l\mathbf{u}_j{}^{(i)}=\lambda\sum_{n=1}^{M}q_n\mathbf{u}_i{}^{(n)}$$

$$\Longleftrightarrow\qquad \sum_{n=1}^{M}\sum_{l=1}^{M}\left(\frac{1}{M}\sum_{n=1}^{N}\mathbf{u_i}^{(\mathbf{n})}\mathbf{u_j}^{(\mathbf{n})}dxdy\right)q_l\mathbf{u_i}^{(\mathbf{n})}=\lambda\sum_{n=1}^{M}q_n\mathbf{u_i}^{(\mathbf{n})}$$

✓ **Eigen value problem of M by M Matrix**

$$\sum_{l=1}^{M}C_{nl}q_l=\lambda q_n \qquad \phi(x)=\sum_{n=1}^{M}q_n u^{(n)}(x)$$

○ $U \approx \sum_{k=1}^{p}\alpha_k\phi^k$

- p is the number of POD modes (basis vectors) used in reconstruction
- Typically $p \ll m$
- α_k are the POD coefficients

Ref) Sirovich, L. (1987). "TURBULENCE ANS THE DYNAMICS OF COHERENT STRUCTURES PART 1: COHERENT STRYCTYRES", *Quarterly of Applied Mathematics*, 45(3), 561-571.

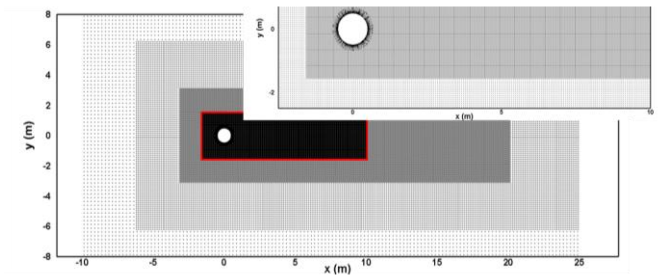
POD with Unsteady Cylinder Flows

Time dependent problem: Cylinder problem

- **CFD Solver: Star-ccm+**

✓ **Determined values**

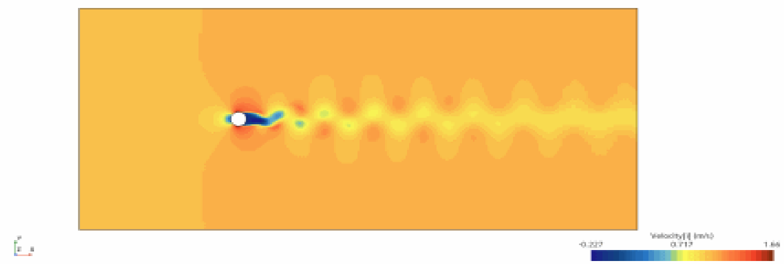
- Diameter of cylinder 1m
- Reynolds Number **67,567**
- No. of grids 260,576



➢ Mesh shape of the cylinder simulation

✓ **Physics model of simulation**

Simulation condition	Value	
Scheme	Spatial	2^{nd} order 3-dimensional
	Temporal	2^{nd} order implicit unsteady
Turbulent Modeling	Turbulent model	Realizable k-ε
	Wall treatment	All y+ wall treatment
Calculation Time	Maximum physical time	300 sec (Converged about 50 sec)
	Delta time	0.01 sec
Fluid	Flow properties	Segregated
	Type	Incompressible Air



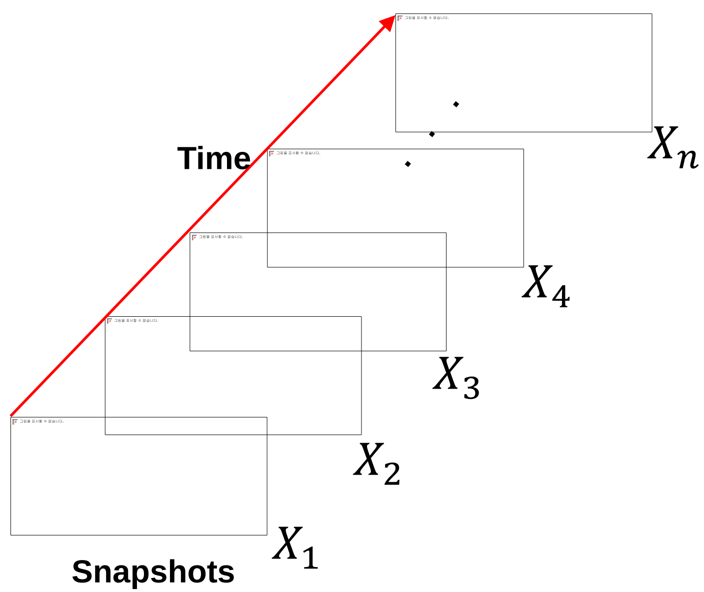
➢ X-velocity(above) and Y-velocity(below) from 200 sec to 210 sec

✓ **Error Calculation**

$$Error = \frac{1}{N}\sum_{i=1}^{N}(y_o - y_i)^2$$

POD with Unsteady Cylinder Flows

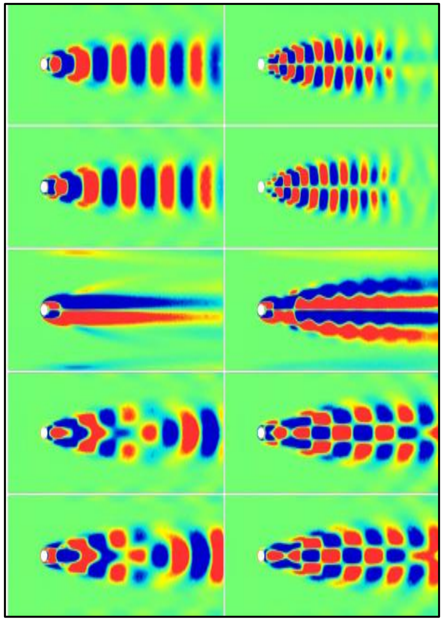
- **Collection of Samples**

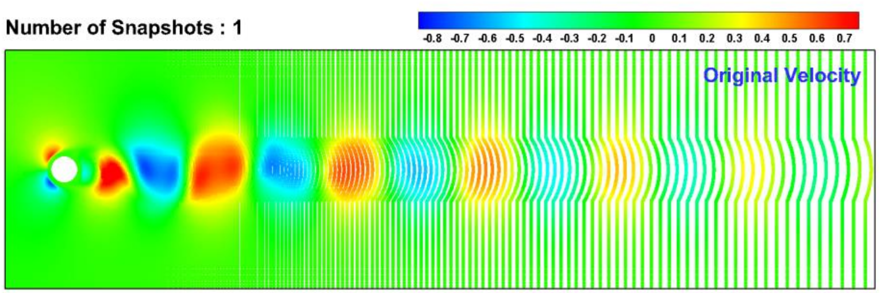


- **Organize as matrix**

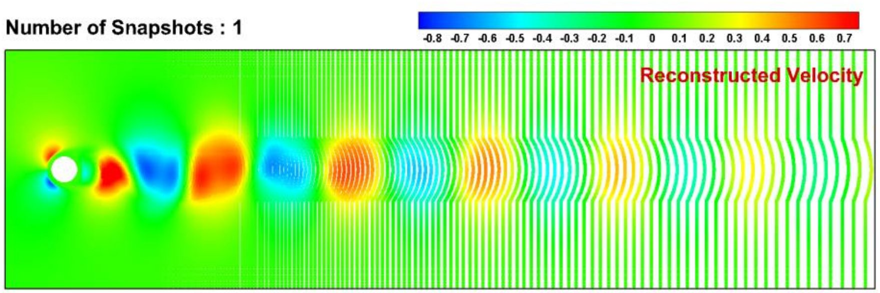
$$\begin{matrix} X_1^1 & X_1^2 & \cdots & X_1^n \\ X_2^1 & X_2^2 & \cdots & X_2^n \\ \vdots & \vdots & \ddots & \vdots \\ X_n^1 & X_n^2 & \cdots & X_n^n \end{matrix}$$

- **Mode decomposition**





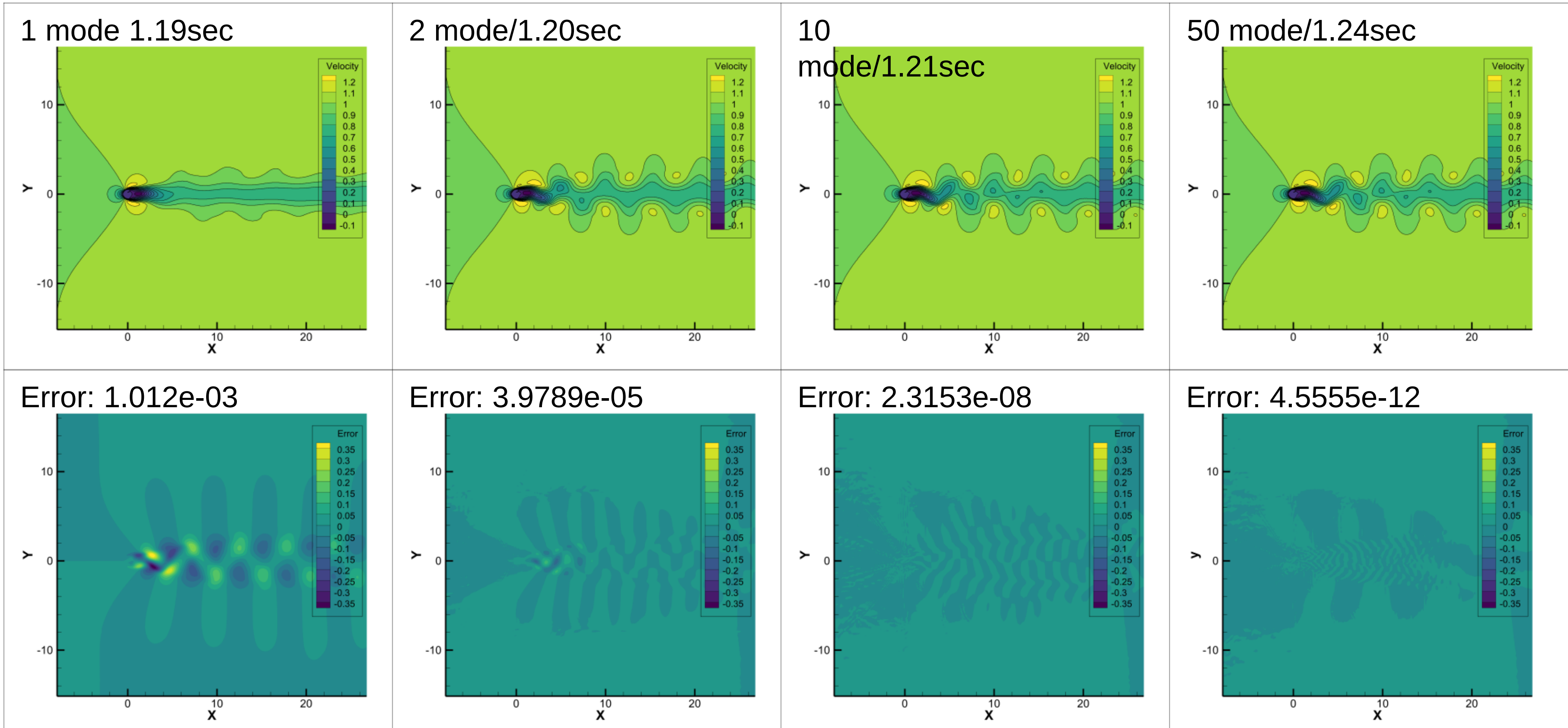
FOM



5-POD reconstructed (99%)

POD with Unsteady Cylinder Flows

Time dependent problem: Cylinder problem – POD mode analysis



Validation: Sloshing case – mild, moderate & violent

- Z. R. Kishev, C. Hu, and M. Kashiwagi (2006) "Numerical simulation of violent sloshing by a CIP-based method", Journal of Marine Science and Technology, 11, 111-122.

➢ Forced horizontal oscillation: $\eta = A\sin(\omega t)$

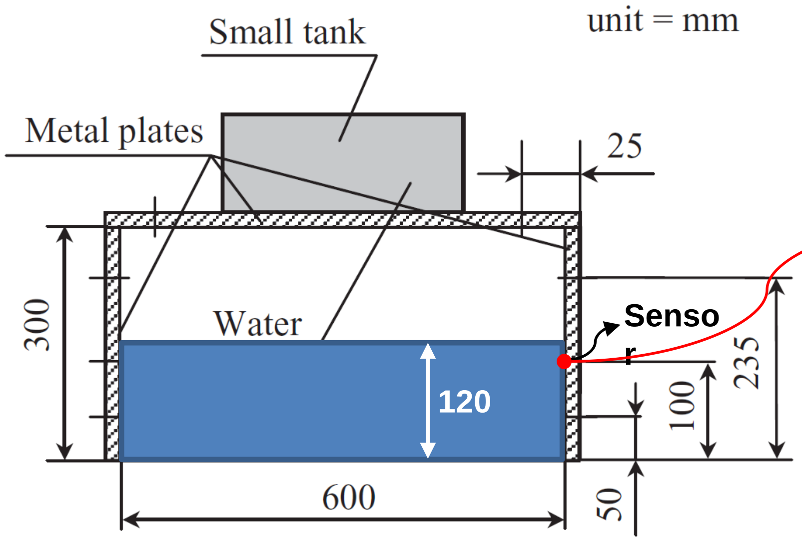
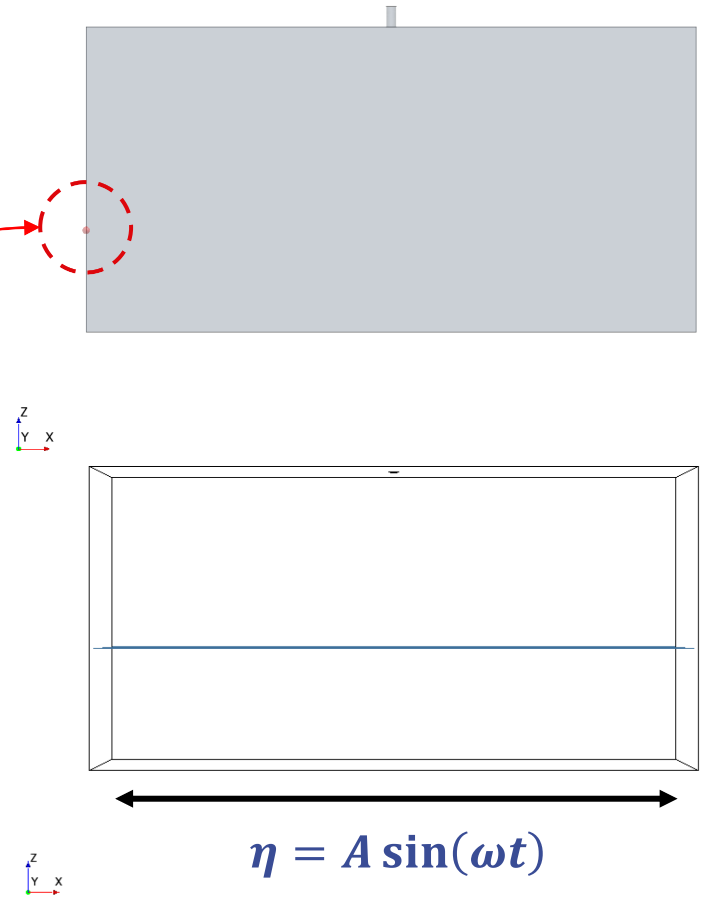


Fig. 1. Schematic view of tank with dimensions and principal pressure gauge positions indicated



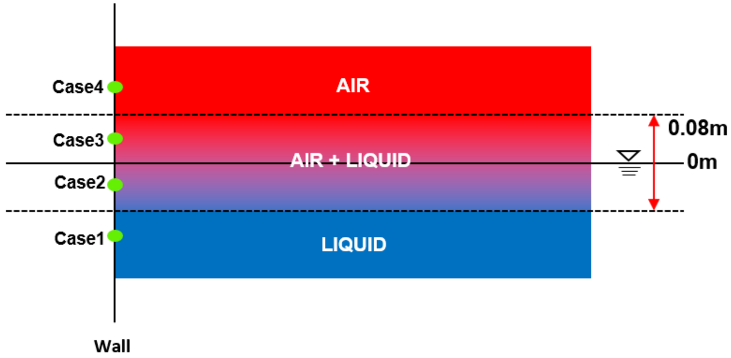
- Water height : 0.12m (filling level: 40%H)
- Sensor height : 0.10m
- Amplitude : 0.05m
- Period : 1.50s (Moderate) , 1.30s (Violent)

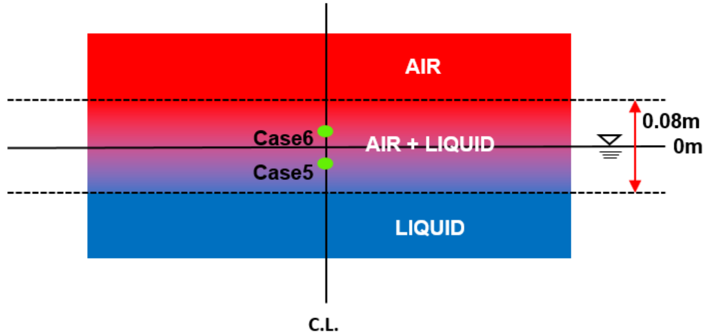
$\eta = A\sin(\omega t)$

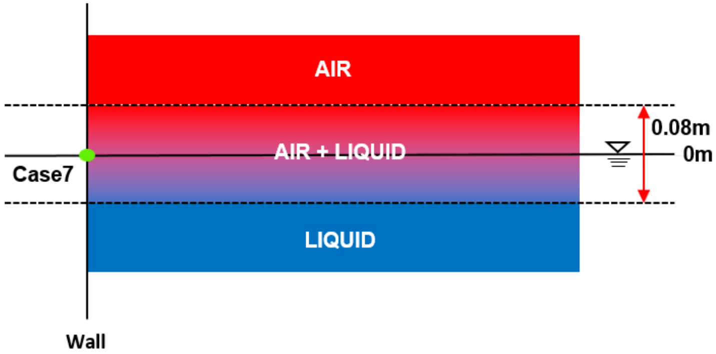
Collaboration with PNU (PI-박종천)

Mild Sloshing

❖ Measuring Position







✓ **Pressure measurement of wall plane (4 Points)**

- Case1 – X = 0m, Z = -0.06m
- Case2 – X = 0m, Z = -0.02m
- Case3 – X = 0m, Z = +0.02m
- Case4 – X = 0m, Z = +0.06m

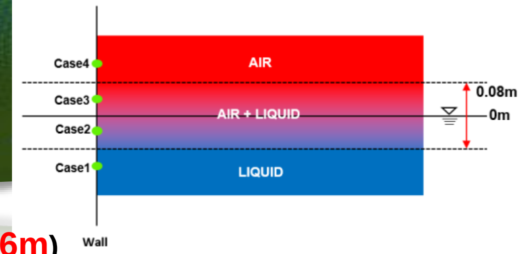
✓ **Velocity measurement (2 Points)**

- Case5 – X = 0.45m, Z = -0.02m
- Case6 – X = 0.45m, Z = +0.02m

✓ **Volume of Fraction measurement of wall plane (1 Points)**

- Case7 – X = 0.0m, Z = 0.0m

Mild Sloshing

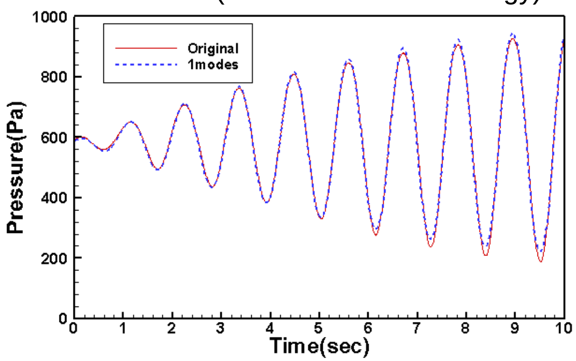


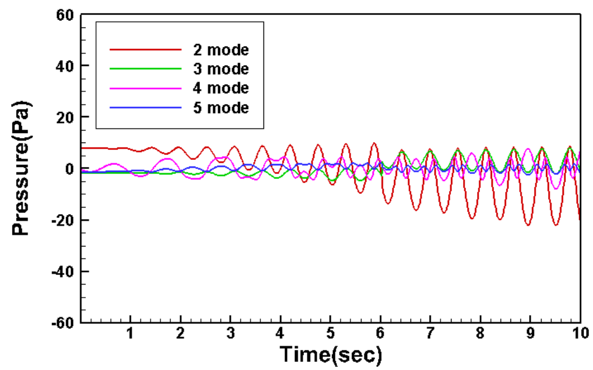
	λ	% Energy
1	0.95247	95.247
2	0.03305	98.553
3	0.00717	99.270
4	0.00364	99.634
5	0.00138	99.772
⋮	...	⋮
15	0.00001	99.991

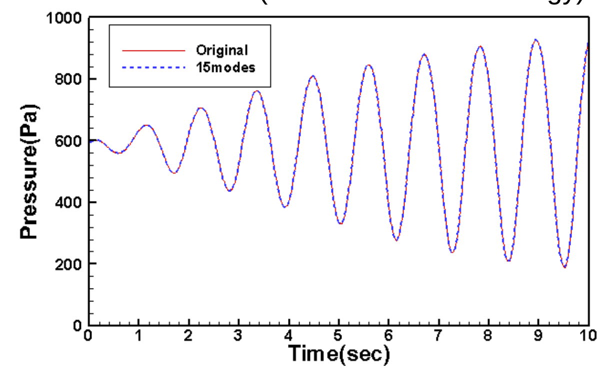
❖ Reconstruction of pressure field (Case1 – X= 0m, Z= -0.06m)

✓ **Comparison of original & reconstructed time series graph**

- **1** mode (*95.247%* of Total Energy)
- **15** modes (*99.991%* of Total Energy)



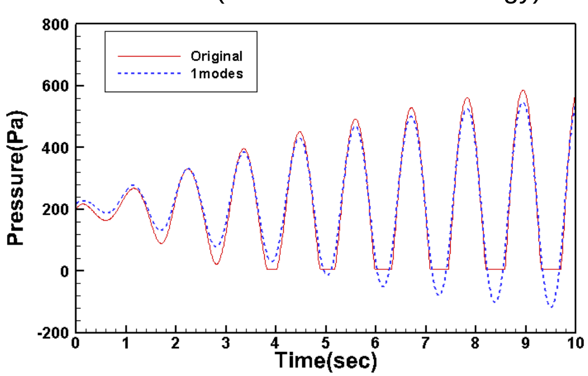


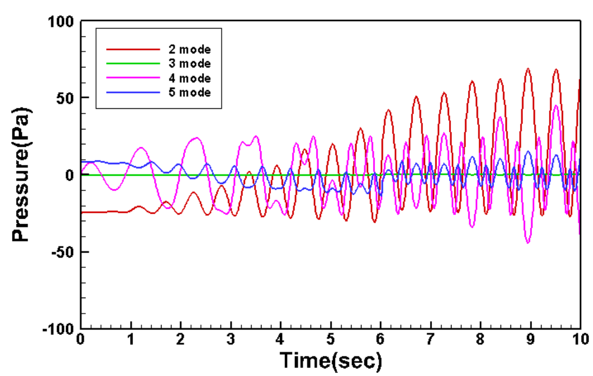


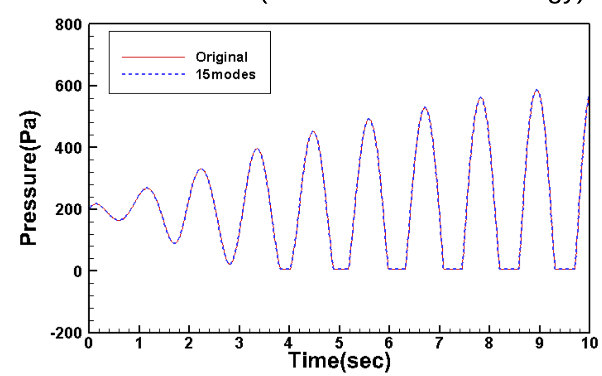
❖ Reconstruction of pressure field (Case2 – X= 0m, Z= -0.02m)

✓ **Comparison of original & reconstructed time series graph**

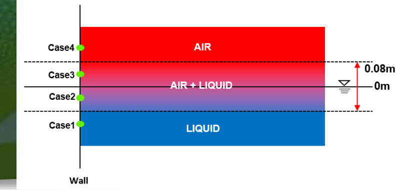
- **1** mode (*95.247%* of Total Energy)
- **15** modes (*99.991%* of Total Energy)







Mild Sloshing

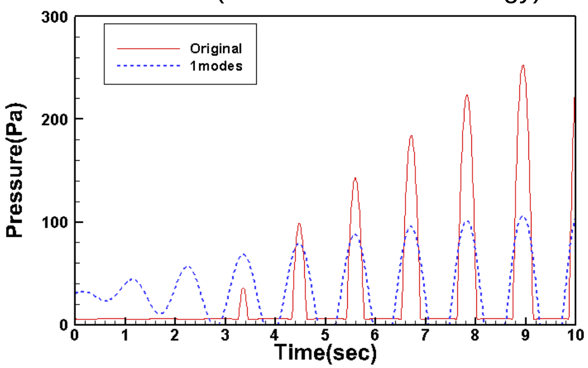


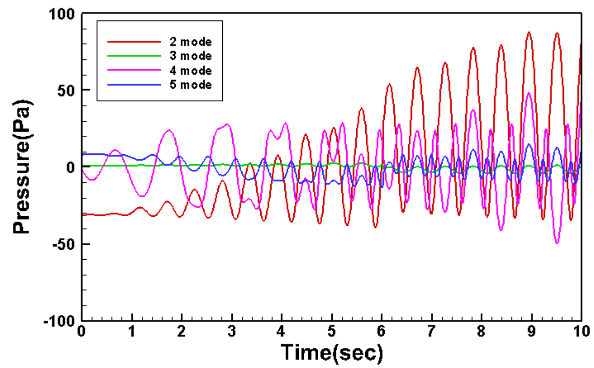
POD modes No	λ	% Energy
1	0.95247	*95.247*
2	0.03305	*98.553*
3	0.00717	*99.270*
4	0.00364	*99.634*
5	0.00138	*99.772*
⋮	…	⋮
15	0.00001	*99.991*

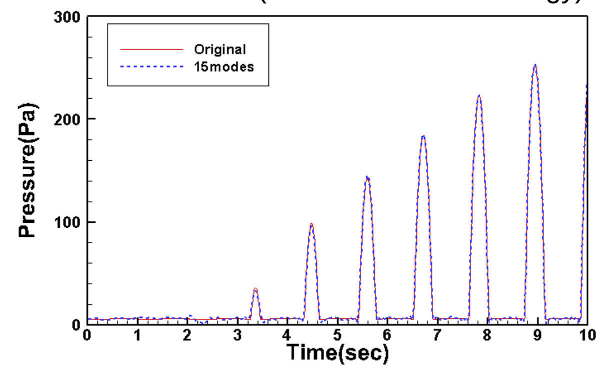
❖ Reconstruction of pressure field (Case3 – X= 0m, Z= +0.02m)

✓ **Comparison of original & reconstructed time series graph**

- **1** mode (*95.247%* of Total Energy)
- **15** modes (*99.991%* of Total Energy)



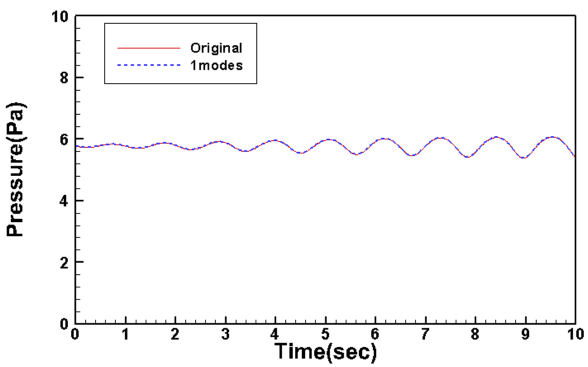


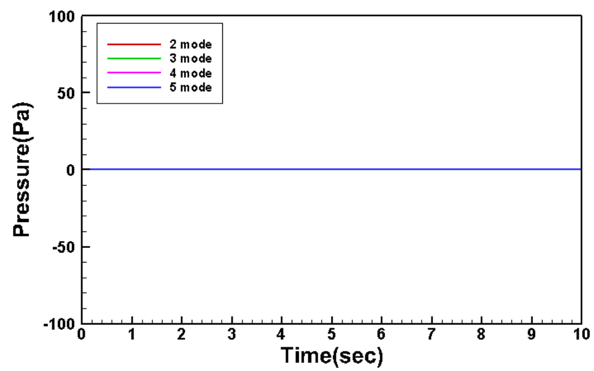


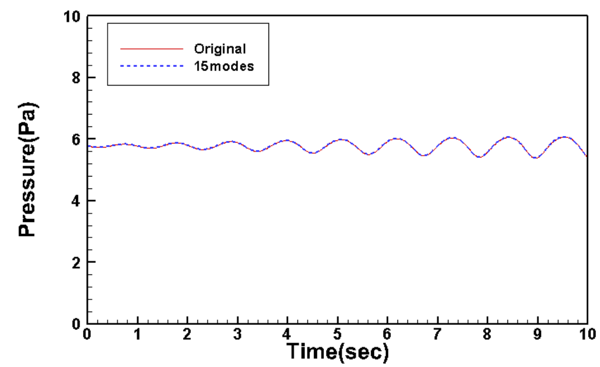
❖ Reconstruction of pressure field (Case4 – X= 0m, Z= +0.06m)

✓ **Comparison of original & reconstructed time series graph**

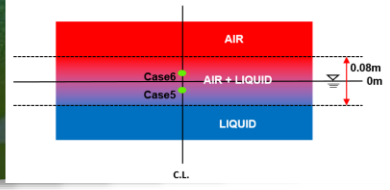
- **1** mode (*95.247%* of Total Energy)
- **15** modes (*99.991%* of Total Energy)







Mild Sloshing

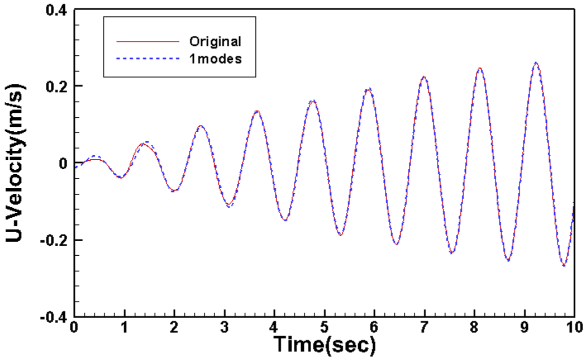


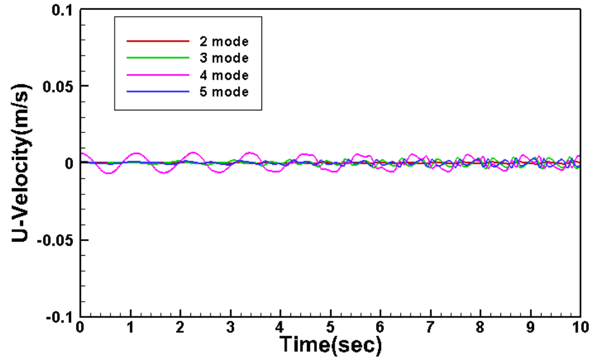
POD modes No	λ	% Energy
1	0.94837	94.837
2	0.02795	96.633
3	0.00790	98.423
4	0.00371	98.795
5	0.00354	99.149
⋮	...	⋮
29	0.00004	99.902

❖ Reconstruction of Velocity field (Case5 – X= 0.45m, Z= -0.02m)

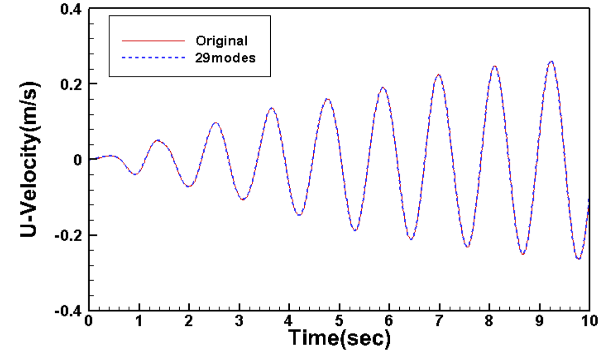
✓ **Comparison of original & reconstructed time series graph**

- **1** mode (***94.837%*** of Total Energy)





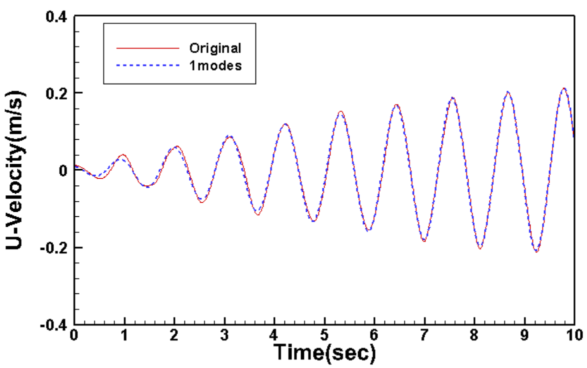
- **29** modes (***99.902%*** of Total Energy)

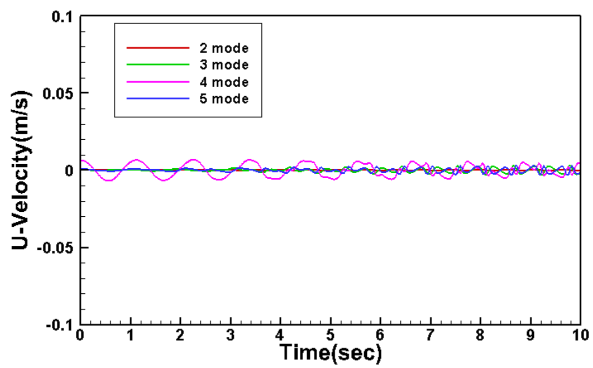


❖ Reconstruction of Velocity field (Case6 – X= 0.45m, Z= +0.02m)

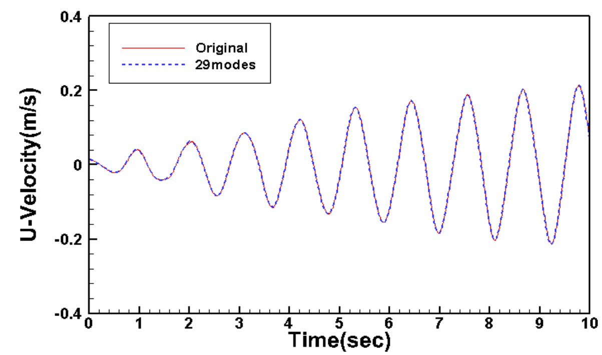
✓ **Comparison of original & reconstructed time series graph**

- **1** mode (***94.837%*** of Total Energy)



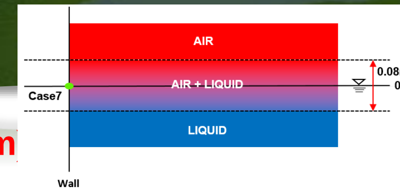


- **29** modes (***99.902%*** of Total Energy)



Mild Sloshing

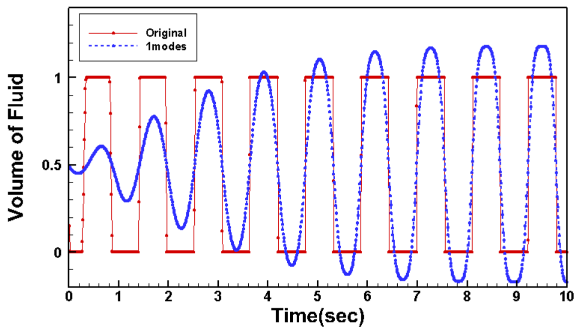
❖ Reconstruction of Volume of Fluid (Case7 – X= 0m, Z=0m)

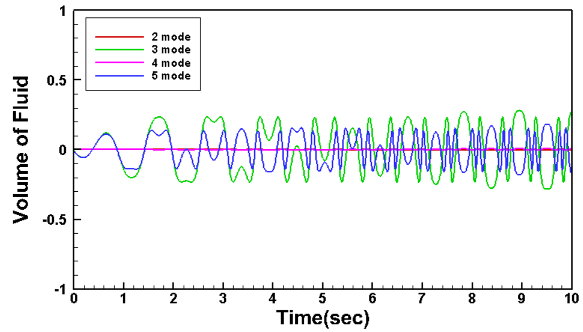


POD modes No	λ	% Energy
1	0.55891	*55.891*
2	0.18461	*74.352*
3	0.07476	*81.828*
4	0.04482	*86.311*
5	0.02740	*89.052*
⋮	...	⋮
177	0.00001	*99.900*

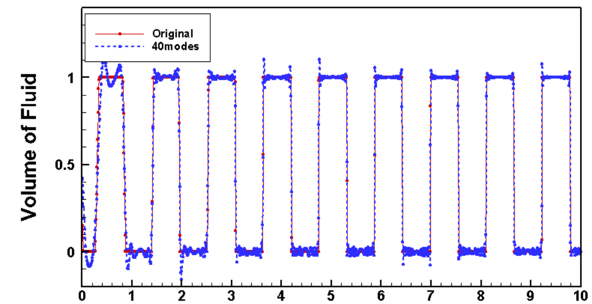
✓ Comparison of original & reconstructed time series graph

- **1** mode (*55.891%* of Total Energy)

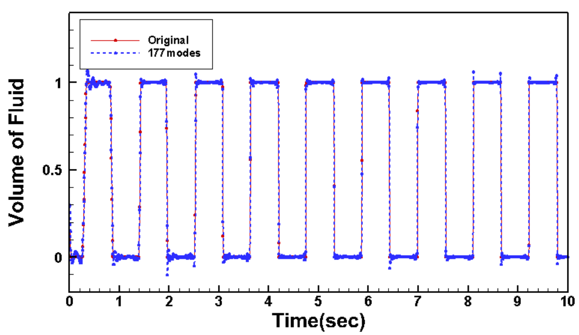




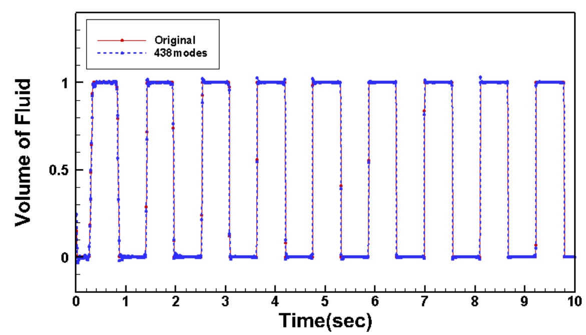
- **40** mode (*99.009%* of Total Energy)



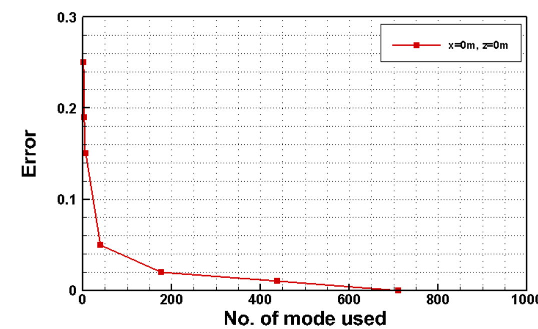
- **177** modes (*99.901%* of Total Energy)



- **438** modes (*99.990%* of Total Energy)



- **RMSE (Root mean square error)**

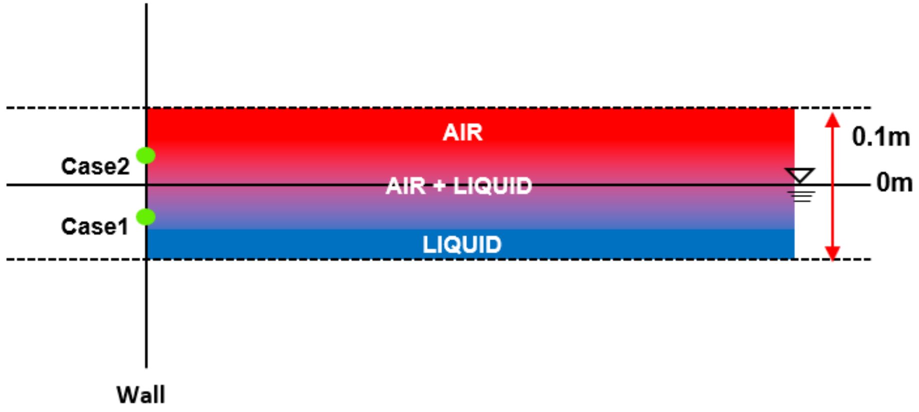


$$Error = \sqrt{\frac{\sum_{i=1}^{n}(p_{POD}^{i} - p_{CFD}^{i})^2}{n}}$$

n = No.of snapshots

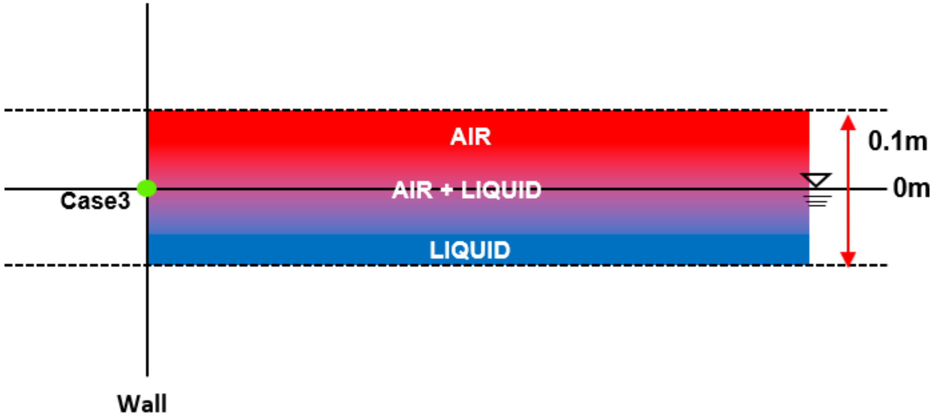
Moderate Sloshing

❖ Measuring Position



✓ **Pressure measurement of wall plane (2 Points)**

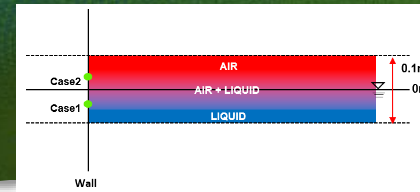
- ➢ Case1 – X = 0.0m, Z = - 0.02m
- ➢ Case2 – X = 0.0m, Z = + 0.02m



✓ **Volume Fraction measurement of wall plane (2 Points)**

- ➢ Case3 – X = 0.0m, Z = 0.0m

Moderate Sloshing

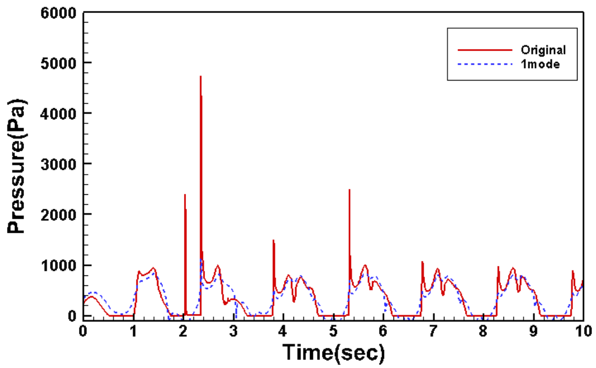


POD modes No	λ	% Energy
1	0.81143	*81.143*
2	0.07640	*88.784*
3	0.02365	*91.149*
4	0.01666	*92.816*
5	0.01416	*94.277*
⋮	...	⋮
286	0.000001	*99.990*

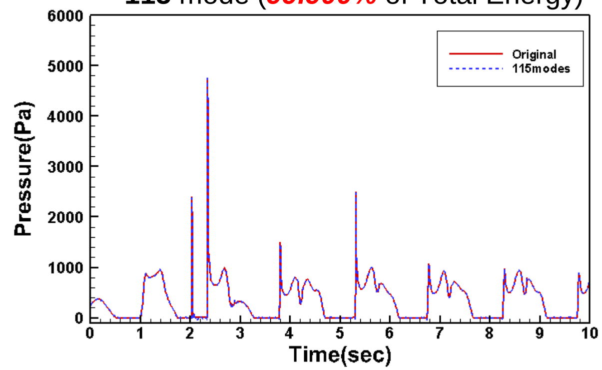
❖ Reconstruction of **pressure** field (Case1 – X= 0m, Z= -0.02m)

✓ Comparison of original & reconstructed time series graph

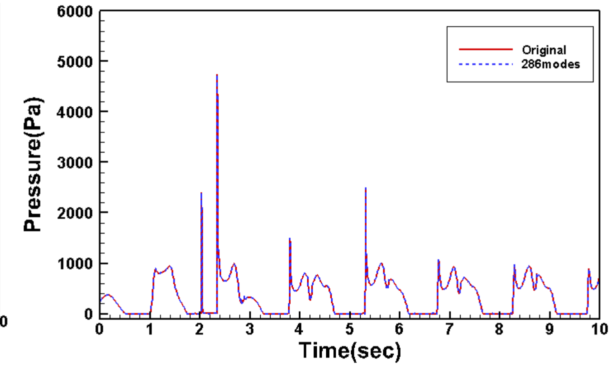
- **1** mode (*81.143%* of Total Energy)



- **115** mode (*99.900%* of Total Energy)



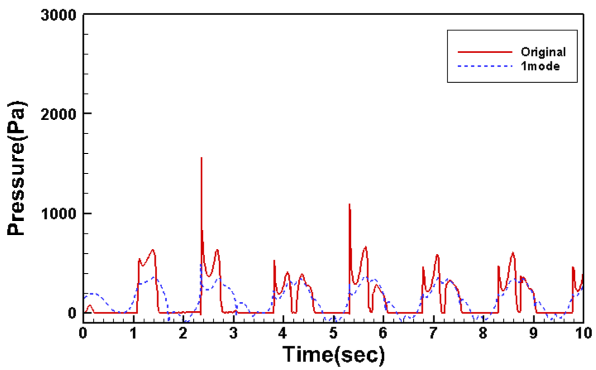
- **286** mode (*99.990%* of Total Energy)



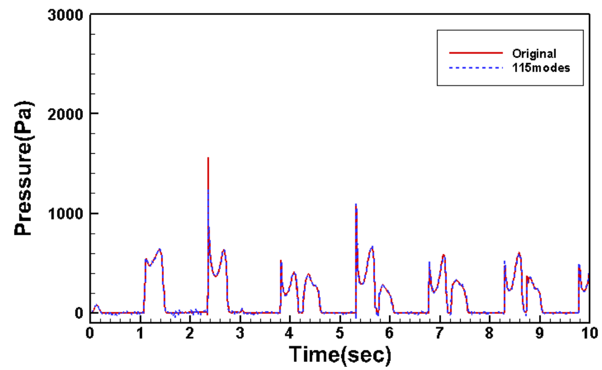
❖ Reconstruction of **pressure** field (Case2 – X= 0m, Z= +0.02m)

✓ Comparison of original & reconstructed time series graph

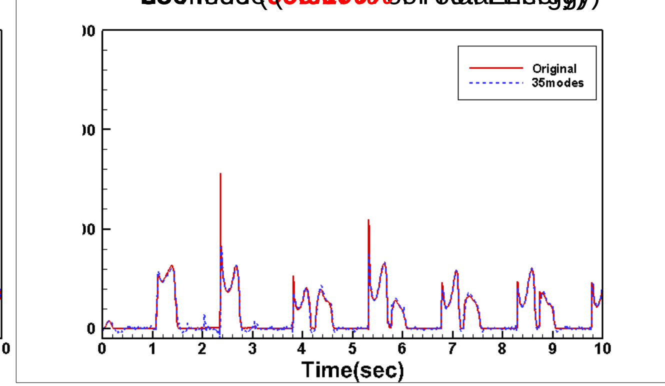
- **1** mode (*81.143%* of Total Energy)



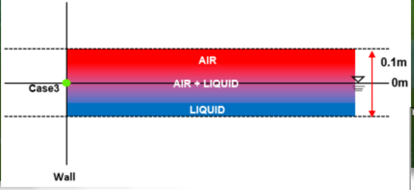
- **115** mode (*99.900%* of Total Energy)



- **286** mode (*99.990%* of Total Energy)



Moderate Sloshing



❖ Reconstruction of Volume of Fluid (Case3 – X= 0m, Z= 0m)

✓ **Comparison of original & reconstructed time series graph**

- **1** mode (***46.043%*** of Total Energy)
- **30** mode (***90.028%*** of Total Energy)
- **316** mode (***99.001%*** of Total Energy)
- **732** mode (***99.900%*** of Total Energy)

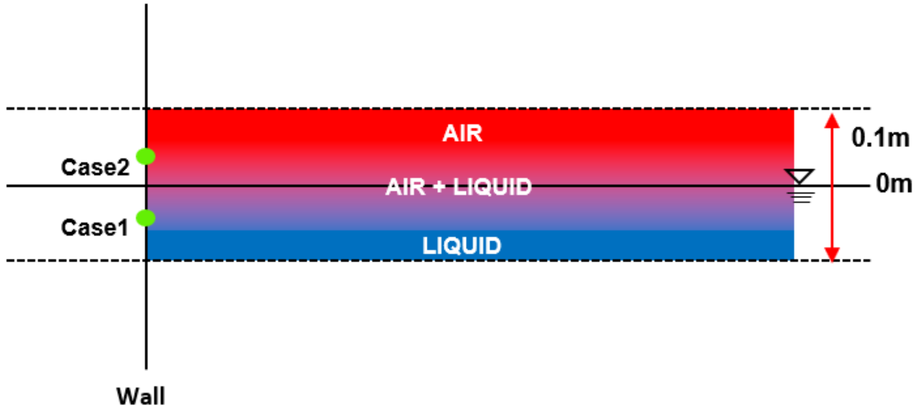
- **RMSE (Root mean square error)**

$$Error = \sqrt{\frac{\sum_{i=1}^{n}(p_{POD}^{i} - p_{CFD}^{i})^2}{n}}$$

n = No.of snapshots

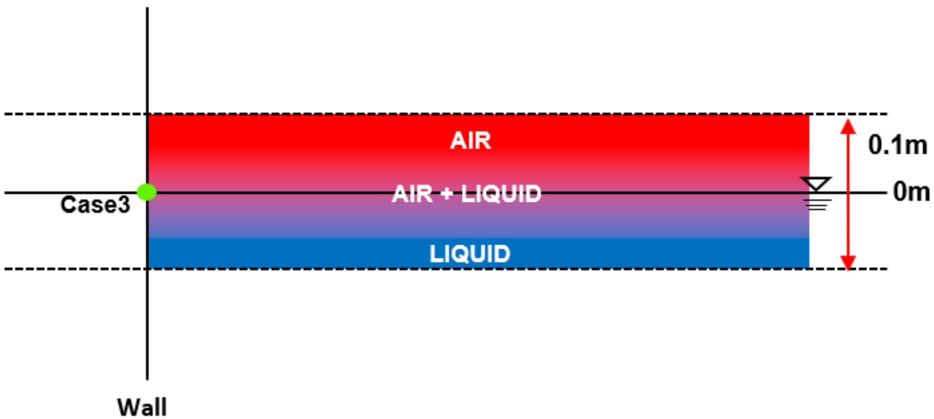
Violent Sloshing

❖ Measuring Position



✓ **Pressure measurement of wall plane (2 Points)**

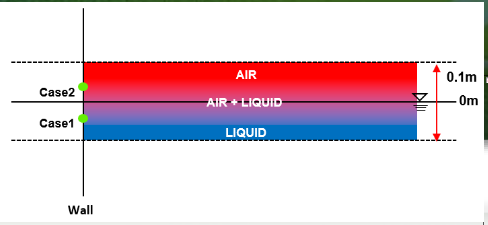
- ➢ Case1 – X = 0.0m, Z = - 0.02m
- ➢ Case2 – X = 0.0m, Z = + 0.02m



✓ **Volume Fraction measurement of wall plane (2 Points)**

- ➢ Case3 – X = 0.0m, Z = 0.0m

Violent sloshing



❖ Reconstruction of pressure field (Case1 – X= 0m, Z= -0.02m)

✓ Comparison of original & reconstructed time series graph

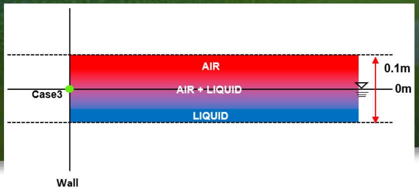
- **1** mode (*77.765%* of Total Energy)
- **131** mode (*99.901%* of Total Energy)
- **351** mode (*99.990%* of Total Energy)

❖ Reconstruction of pressure field (Case2 – X= 0m, Z= +0.02m)

✓ Comparison of original & reconstructed time series graph

- **1** mode (*77.765%* of Total Energy)
- **131** mode (*99.901%* of Total Energy)
- **351** mode (*99.990%* of Total Energy)

Violent sloshing



❖ Reconstruction of Volume of Fluid (Case3 – X= 0m, Z= 0m)

✓ **Comparison of original & reconstructed time series graph**

- **1** mode (***52.329%*** of Total Energy)
- **17** mode (***90.128%*** of Total Energy)
- **295** mode (***99.004%*** of Total Energy)
- **715** mode (***99.900%*** of Total Energy)
- **RMSE (Root mean square error)**

$$Error = \sqrt{\frac{\sum_{i=1}^{n}(p_{POD}^{i} - p_{CFD}^{i})^2}{n}}$$

n = No.of snapshots

Efficiency and Accuracy of POD Analysis

❖ Sloshing problem

- Through **CFD-Snapshot based POD**, the order can be reduced by analyzing the sloshing(Mild, Moderate, Violent) problem and extracting the important mode.

❖ POD analysis of sloshing

- Since the computation efficiency and accuracy of POD is affected by the No.of snapshots, it is important to use an appropriate No.of snapshots.
- The more intense the sloshing motion, the greater the number of modes used.
  - In all cases, POD mode 1 plays the most dominant role, and it can be seen that the energy level of the flow field using one mode in Mild sloshing is higher compared to Moderate and Violent.
  - Moderate & Violent sloshing should use more mode than Mild sloshing.
- The flow field can be reconstructed using key modes through POD analysis.

	Pressure(**99.99%**)	**Velocity**(**99.9%**)	**Volume of Fluid**(**99.9%**)
Mild	**15** modes	**29** modes	**177** modes
Moderate	**286** modes	**561** modes	**732** modes
Violent	**331** modes	**576** modes	**715** modes

- In special cases, it is also possible to determine the total energy mode of the flow field at one point. (pressure gauge point, free surface check, etc.)

LSTM for Prediction at Untested Time

❖ ANN algorithm for time series – LSTM(Long Short-Term Memory)

➢ Principle of LSTM

- A type of Recurrent Neural Network(RNN)
- The algorithm for learning time series data
- Consisting of input gate, output gate, and forget gate
- Storage of long-term memory(cell state) through forget gate
- Overcoming the vanishing long term problem in typical RNN
- Good performance at predicting, but complicated structure

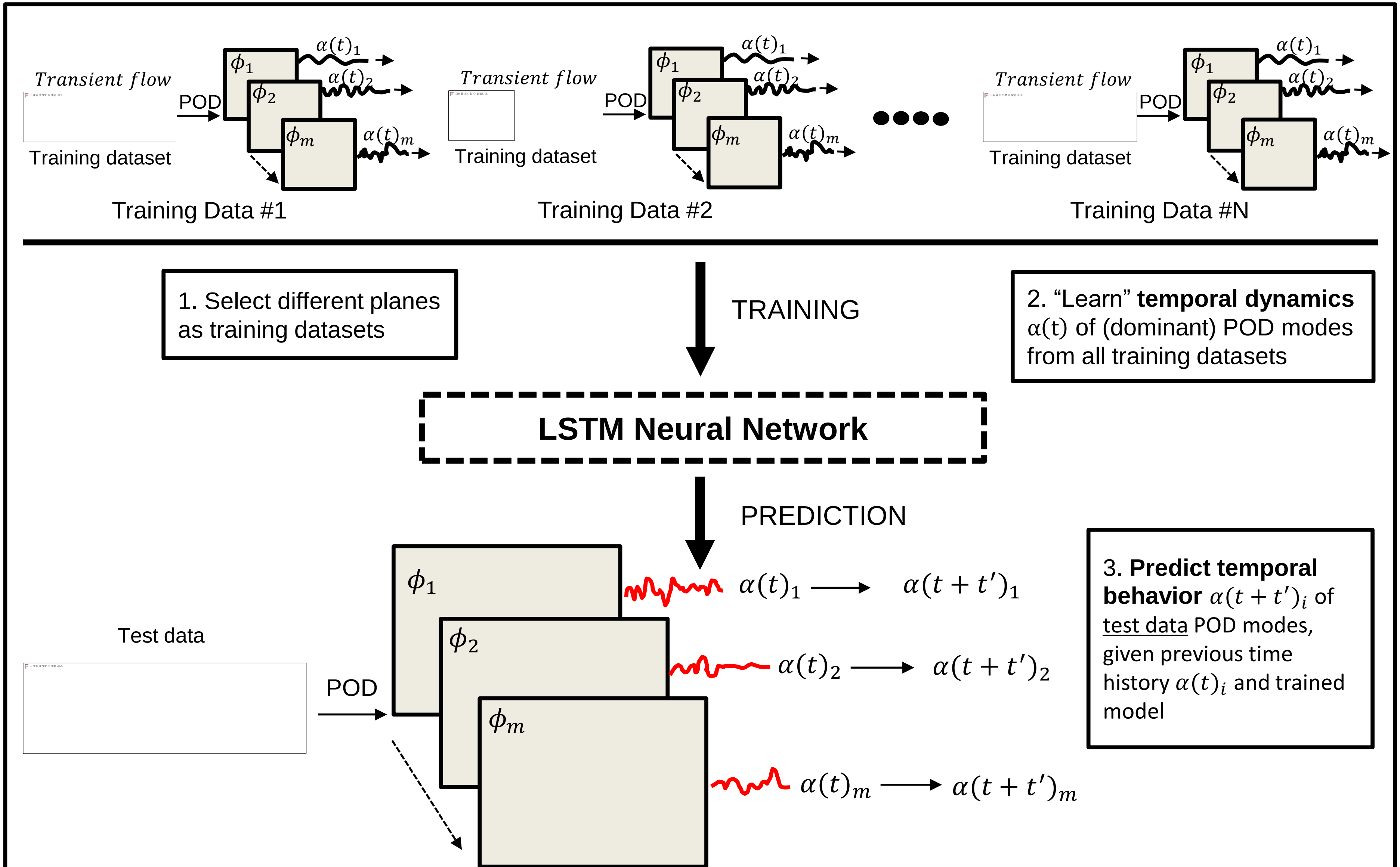
➢ Mechanism of LSTM cell

- Reference

Long Short-Term Memory : From Zero to Hero with PyTorch, FloydHub Blog

LSTM for Prediction at Untested Time

❖ Conceptual view of ROM using LSTM Neural Network



Mild Sloshing Case

❖ **Pressure (Energy : 99.99% , Modes : 15)**

➢ Original Value

➢ POD Value

➢ POD+LSTM Value

➢ RMSE (POD)

➢ RMSE (POD+LSTM)

Moderate Sloshing Case

❖ **Pressure (Energy : 99.99% , Modes : 286)**

➢ Original Value

➢ POD Value

➢ POD+LSTM Value

➢ RMSE (POD)

➢ RMSE (POD+LSTM)

Violent Sloshing Case

❖ **Pressure (Energy : 99.99% , Modes : 331)**

➢ Original Value

➢ POD Value

➢ POD+LSTM Value

➢ RMSE (POD)

➢ RMSE (POD+LSTM)

Accuracy vs. Efficiency

- Number of POD modes for 99.99% energy level

- Total Elapsed Time for Calculation

	Only CFD (STAR-CCM+)	POD+LSTM (All Process)	POD+LSTM (Only Prediction)	Hardware Specification
Mild	15,627 sec	3,245 sec	65 sec	Only CFD : Intel core I9-9960X POD+LSTM : Nvidia RTX 3080
Moderate	41,055 sec	14,868 sec	548 sec	
Violent	42,087 sec	15,932 sec	650 sec	

Shape Design by POD-GPR: Time-Independent, Shape Varying Problems

- Steady, shape varying problem: 2D Transonic Airfoil flows

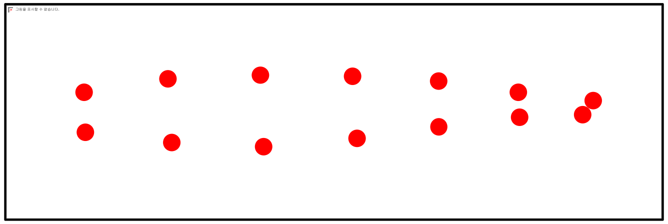
  - **CFD Solver: Stanford University multi-block (SUmb)**
    - Governing Equations: Inviscid Euler, cell-centered FVM
    - Spatial Discretization: 2nd order centered differencing with JST dissipation scheme
    - Temporal integration: 2nd order backward difference formulation
    - Shape parameterization: Hicks-Henne Bump function, Latin hypercube sampling

Mach	AoA	Grid	Solver
0.725	2.92°	351×51 (C-type)	SUmb (Inviscid Euler)

➢Flow simulation setting

Airfoil	Bump no.	Deform range
RAE2822	14	1%

➢Shape deformation setting



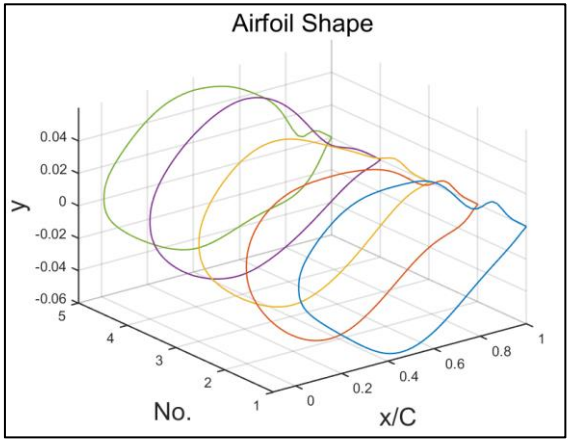
➢RAE2822 Airfoil Bump location

➢RAE2822 Airfoil

POD with Shape Parameters

- Time independent, shape varying, problem: 2D Transonic Airfoil flows

(source: Sabater et al.)



➢ H-H Bump Function

➢ Deformed Airfoil

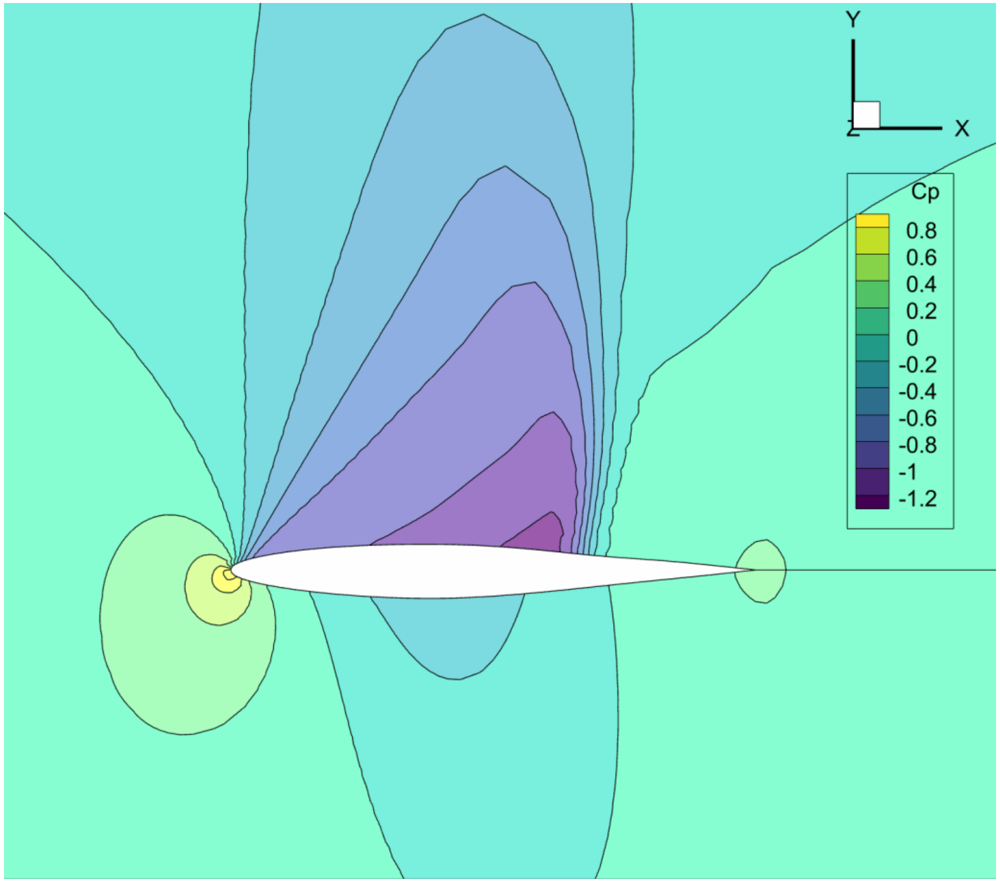
- The airfoil was parameterized by using the following H-H Bump function

$$y = y_{base} + \sum_{i}^{n} \mu_i b(x_i)$$

- t_1 is the location of the maximum bump and t_2 is the width of the bump.
- Using Latin-Hypercube Sampling, randomly transform μ_i to create snapshot data set consisting of various airfoil

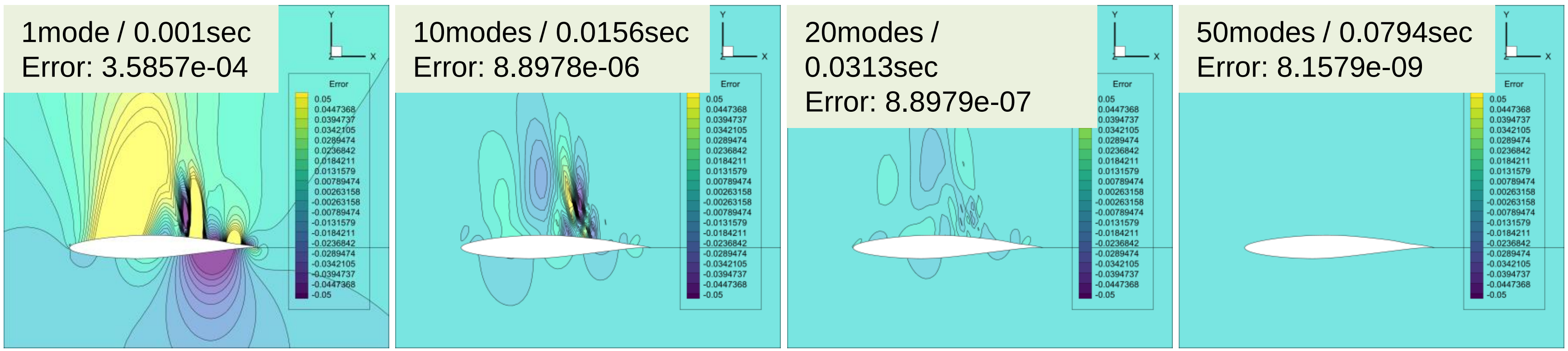
Shape Design with POD-GPR: Time-Independent, Shape Varying Problems

- Steady, shape varying problem: 2D Transonic Airfoil flows

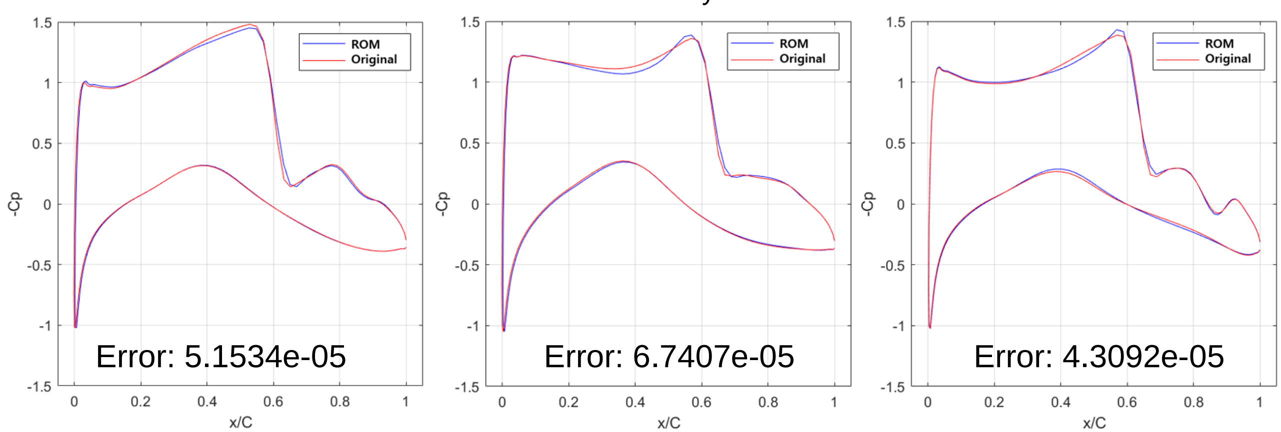


Shape Design with POD-GPR: Time-Independent, Shape Varying Problems

- Steady, shape varying problem: 2D Transonic Airfoil flows – POD-GPR Results



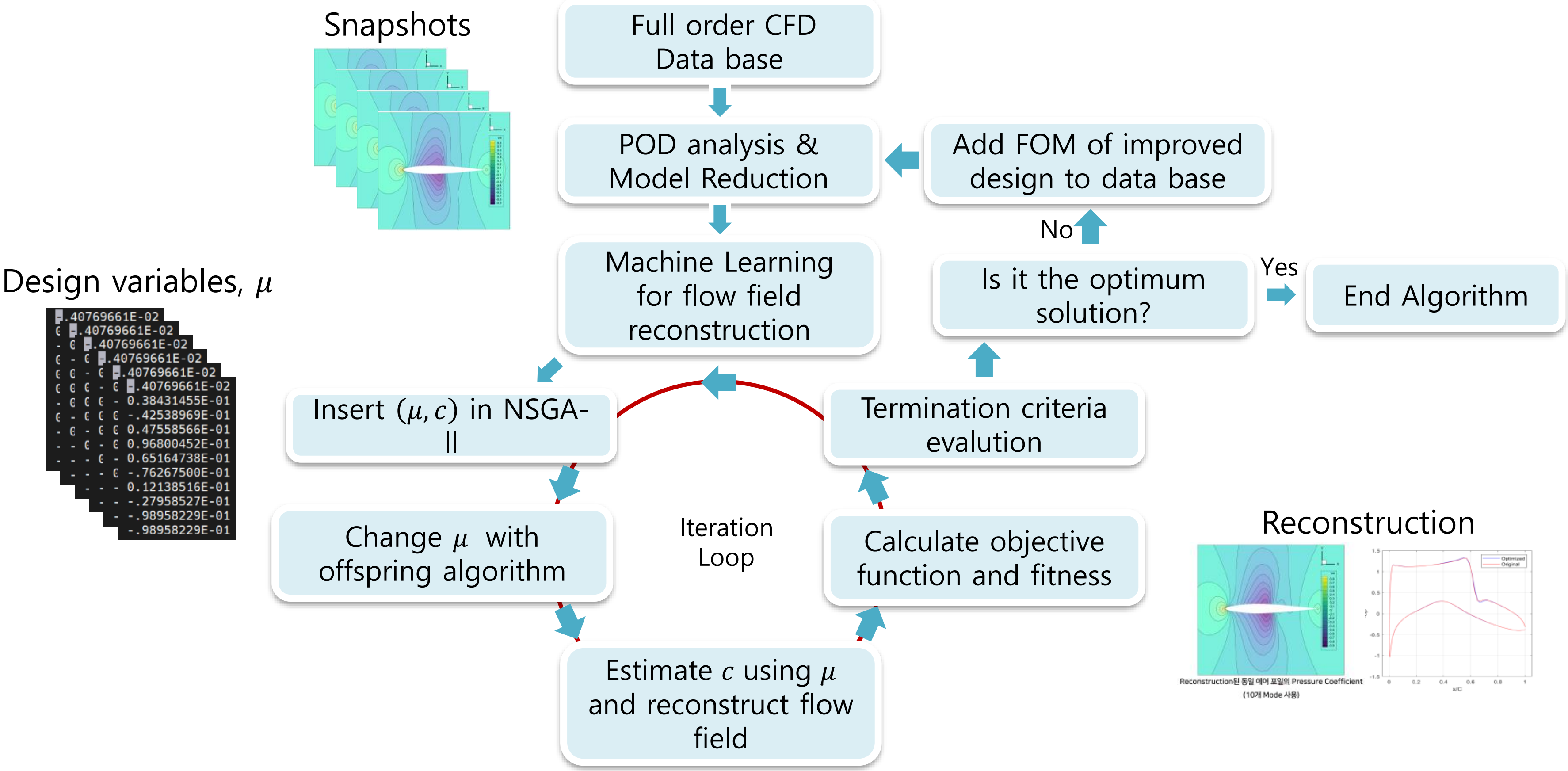
➢ POD analysis



➢ Results of ROM for different design cases reconstructed by 38 modes

Shape Optimization Process

- Optimization Loop



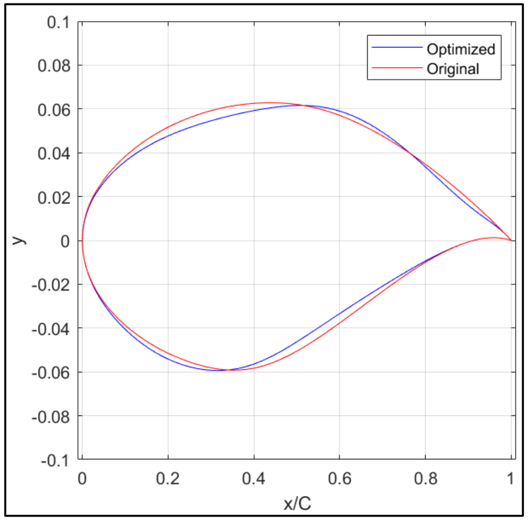
Pros:

(1) No CFD is needed during iterations,

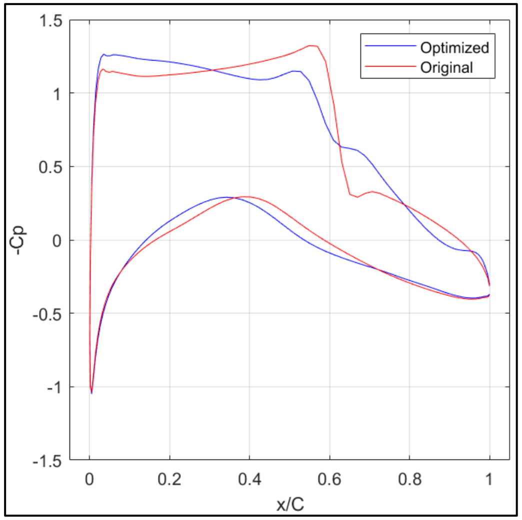
(2) Flow field data available at each iteration

Design with POD-GPR: Time-Independent, Shape Varying Problems

- Transonic wave drag minimization – ***POD-GPR***



➢ Optimized Airfoil

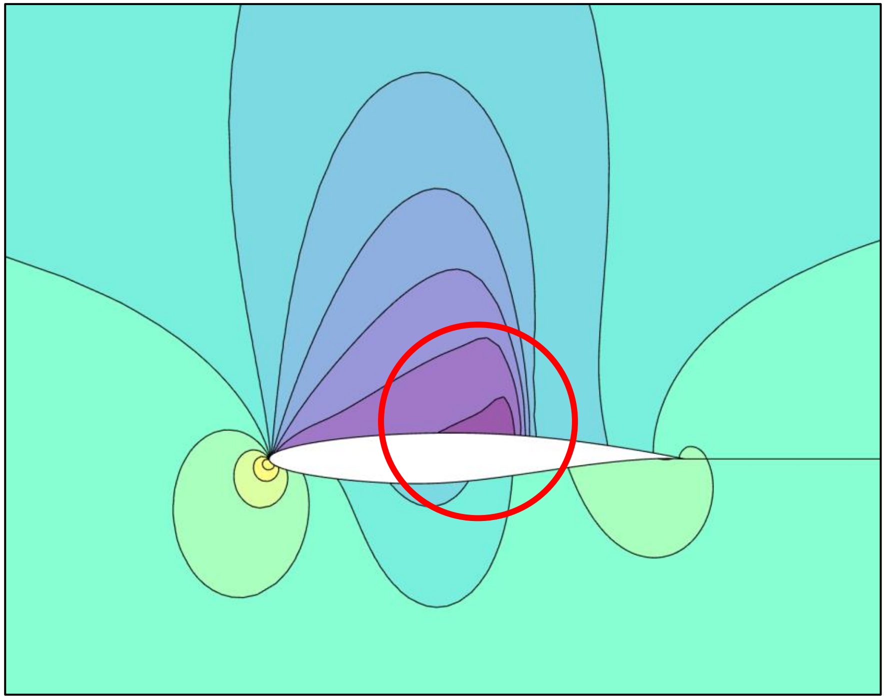


➢ Optimized -Cp plot

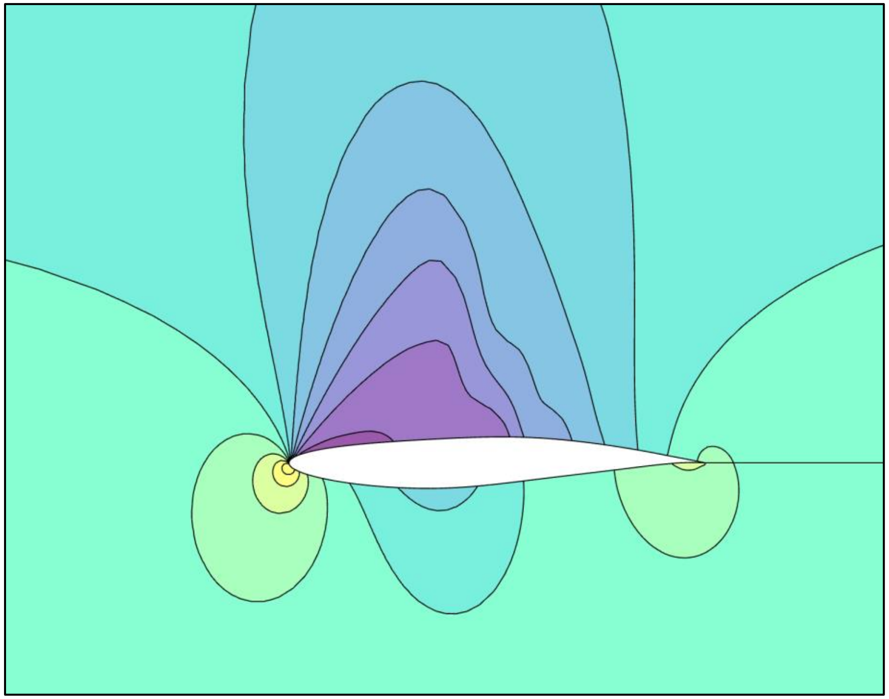
	Original	Optimized	Difference
Cd	0.01239	0.00682	- 44.51%
Cl	0.86292	0.86178	- 0.13%

Design with POD-GPR: Time-Independent, Shape Varying Problems

- Transonic wave drag minimization - Optimization Result



➢ Original Flow Field



➢ Optimized Flow Field

POD with Shape Parameters

Calculation time comparison between FOM and ROM

- Time independent, shape varying, problem: 2D Transonic Airfoil flows

Method		Sec
Full Order Model CFD		**240**
POD-GPR	Modal reduction	32.89
	Learning & Prediction	4.39
	Reconstruction	**0.55**
	Total	**37.83**

➢ Comparison between FOM CFD and POD-GPR reconstruction runtime

- CFD is measured at 240 seconds and POD-GPR is measured at 38 seconds. (6.3% of CFD)
- Reconstruction time is 0.55 seconds and it is expected to be faster during optimization because ML and MR execute only once and data load time is excluded
- Also error was very small, with an average of 1e-05

Contents

I. POD-based Reduced Order Model

- **Dimensionality reduction shape and time**
- **POD-GPR (Shape) vs. POD-LSTM (Time)**

II. Deep neural network (DNN) based Reduced Order Model

- **Convolutional Neural Network – U Net**
- Time, Flow conditions (Mach or AOA), and Shape
- Generative Adversarial Network for Design

Convolution neural network (CNN, 합성곱 신경망)

- CNN은 인간의 시신경 구조를 모방한 신경망으로 이미지를 인식하고 패턴을 학습하는 것에 특히 유용하여 자율주행 자동차, 얼굴인식과 같은 컴퓨터 비전 분야에 많이 사용되고 있다.

- Fully connected layer 만으로 구성된 인공 신경망에 이미지를 학습시키는 경우, 3차원(RGB) 이미지를 1차원으로 평면화 시켜야하며, 이때 발생하는 이미지의 위치 정보 유실로 인해 학습 성능이 떨어지는 한계가 있으나 CNN은 이런 한계점을 보완한 신경망이다.

- CNN은 아래 그림과 같이 이미지의 특징을 추출하는 부분과 분류하는 부분으로 나눌 수 있다. Convolution layer 와 pooling layer를 쌓아 이미지 특징을 추출하고(feature extraction), FC layer를 이용해 특징을 분류한다.

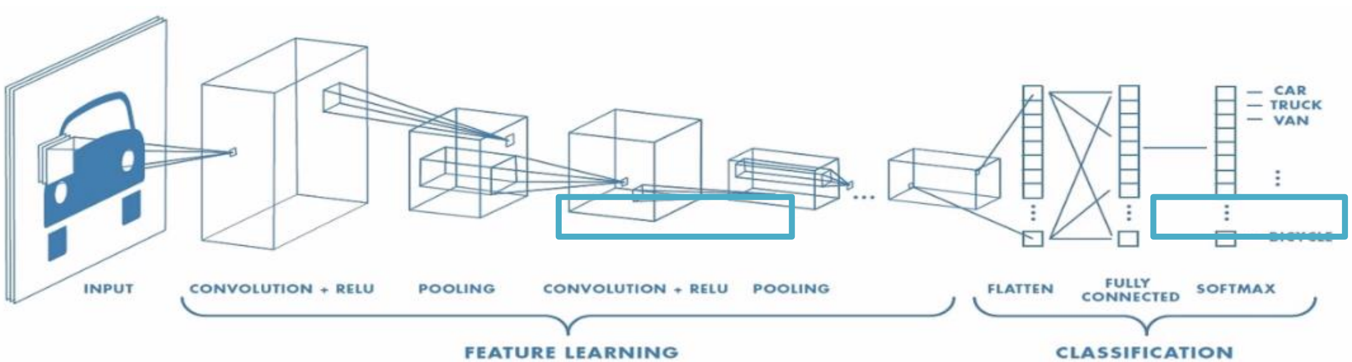
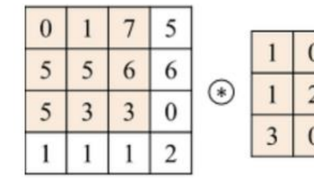


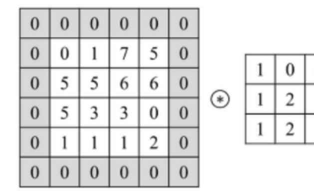
Fig. Overall Structure of CNN

Convolution layer

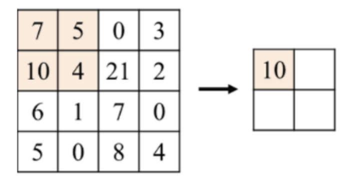
Filter

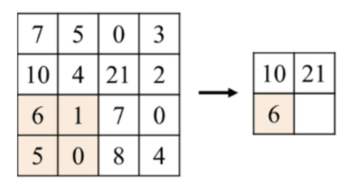


Padding



Pooling layer





Conditional U-Net (Encoder-Decoder)

- U-net은 **battle neck layer**를 기준으로 U자 대칭 형태를 이루고 있으며, 인코더와 디코더로 구성되어 있다.
- U-net은 저차원 정보만을 이용해 고차원으로 복원하는 Auto-Encoder(AE)와는 달리 디코딩 시 저차원은 물론 인코딩에 사용한 고차원 특징 정보를 모두 사용한다. (그림의 빨간 원)
- 이러한 특징으로 인해 기존 CNN에 비해 고해상도 이미지 복원이 가능하며, 인코딩 시 손실되는 객체의 정확한 위치정보 파악이 가능하다.
- Conditional U-net의 경우 특정 조건(Condition)을 추가하여 사용자가 원하는 방향으로 출력 생성에 영향을 줄 수 있다.

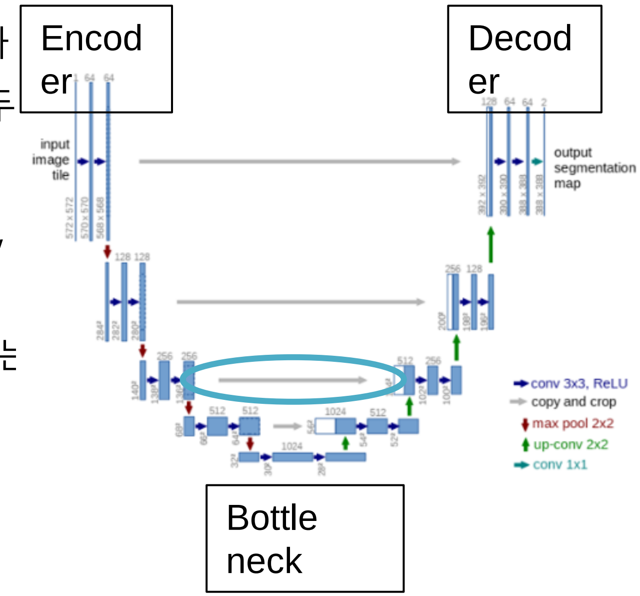


Fig 1. Structure of typical U-Net

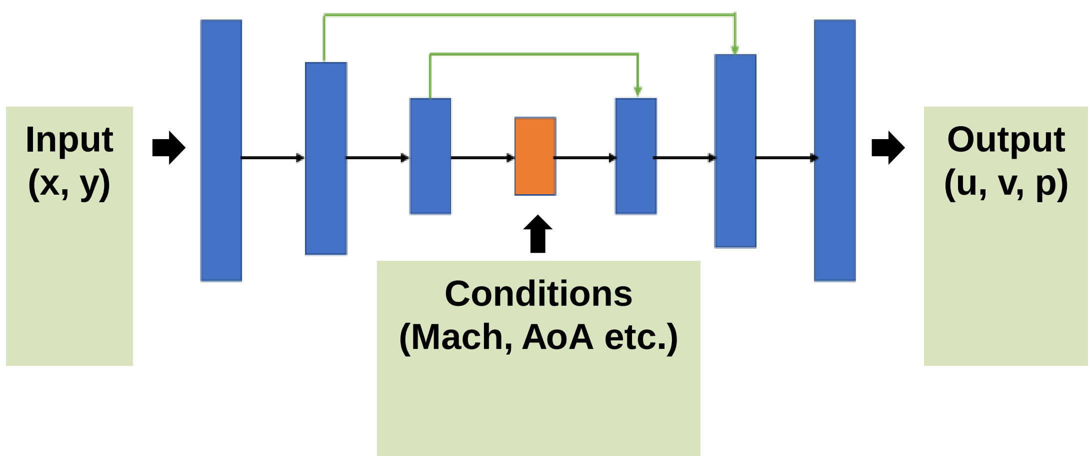


Fig 2. Structure of Conditional U-Net

U Net for Time Parameters

- Data information : eppler387, AoA=16, Mach=0.6
- Time step : t = 10~18 (non-dimensional), total 80 time steps (dt=0.1)
- Train data: 20 (10.1, 10.5, 10.9 … 17.7, validation 10%)
- Test data : 20 (10.3, 10.7, 11.1 … 17.9)

POD-GPR

Conditional U-Net

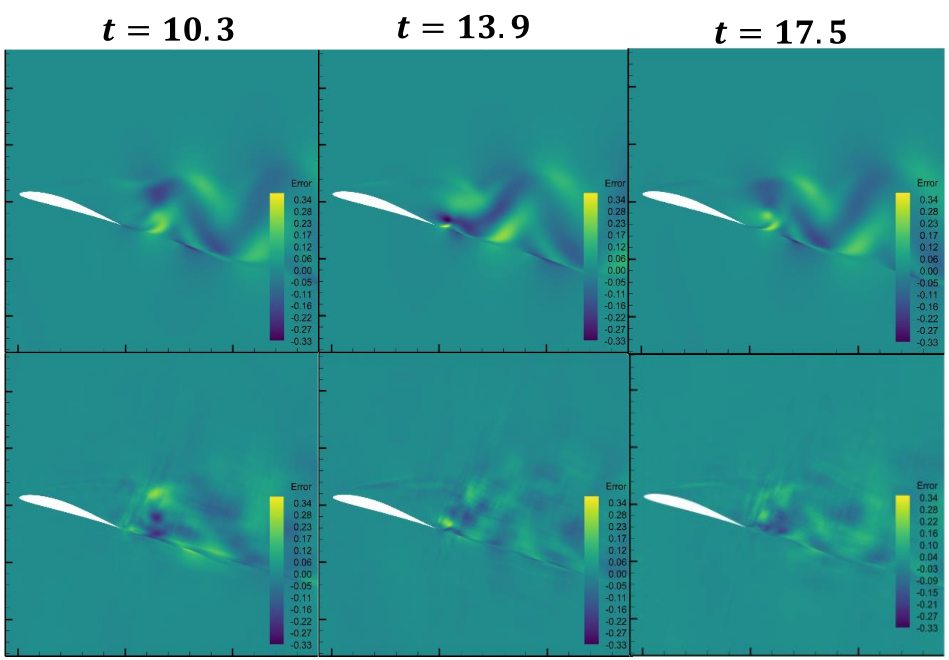


Fig 1. **Error contour** of Predicted x-velocity error contour

CFD 계산 시간: 4hr (for t = 0~18)

GPR 학습 시간 : 37.28 sec

GPR 유동장 예측시간 : 0.55 sec

Unet 학습시간 : 3 hr (학습조건 따라 상이)

Unet 유동장 예측시간 : 0.73 sec

	POD-GPR	Conditional U-Net
u	3.47%	2.96%
p	1.08%	0.86%

Table 1. Mean relative error

U Net for Flow Condition Parameters

- Data information : NACA0012, AoA=0~7(0.5), Mach=0.3~0.5(0.025), 15 AoAs x 9 Mach= <u>135 flow fields</u>
- Train data: 123 (validation 10%)
- Test data : 12

	Mach 0.325 AoA 1.5°	Mach 0.375 AoA 4°	Mach 0.425 AoA 6.5°

POD-GPR

Conditional U-Net

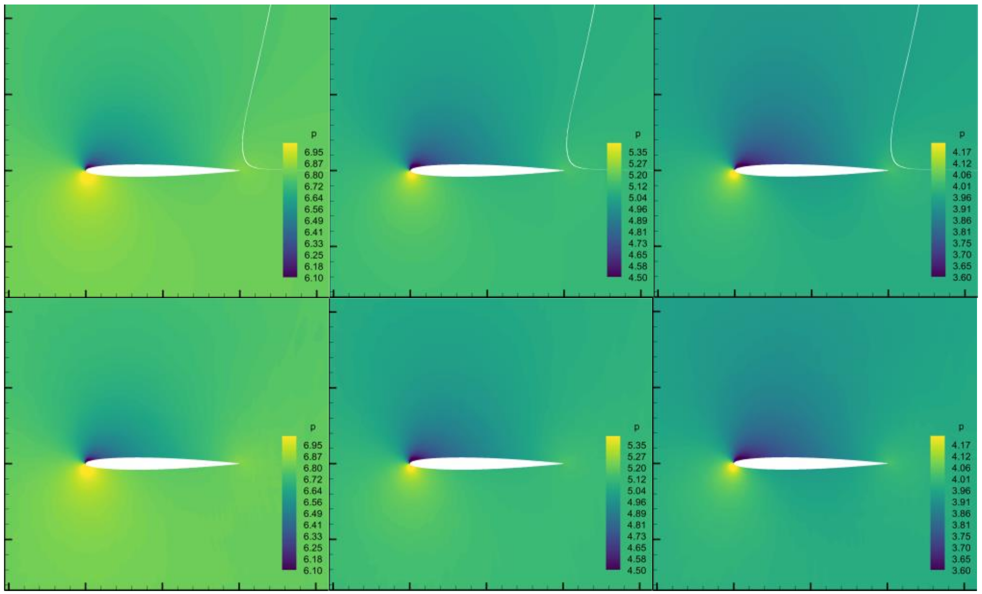


Fig 1. Predicted pressure coefficient contour at various flow condition

CFD 계산 시간: 252 sec (for 1 case)

GPR 학습 시간 : 32.96 sec
GPR 유동장 예측시간 : 0.55 sec

Unet 학습시간 : 1.7 hr (학습조건 따라 상이)
Unet 유동장 예측시간 : 0.73 sec

	POD-GPR	Conditional U-Net
u	0.11%	0.39%
p	0.045%	0.091%

Table 1. Relative error

U Net for Shape & Flow Condition Parameters

- Total number of data set : UIUC 500 shapes x 26 AoAs = 13000 flow fields
- Training data : 12900 (validation 10%)
- Test data : 100 (random 20 shapes x AoA 3, 6, 9, 12, 15)

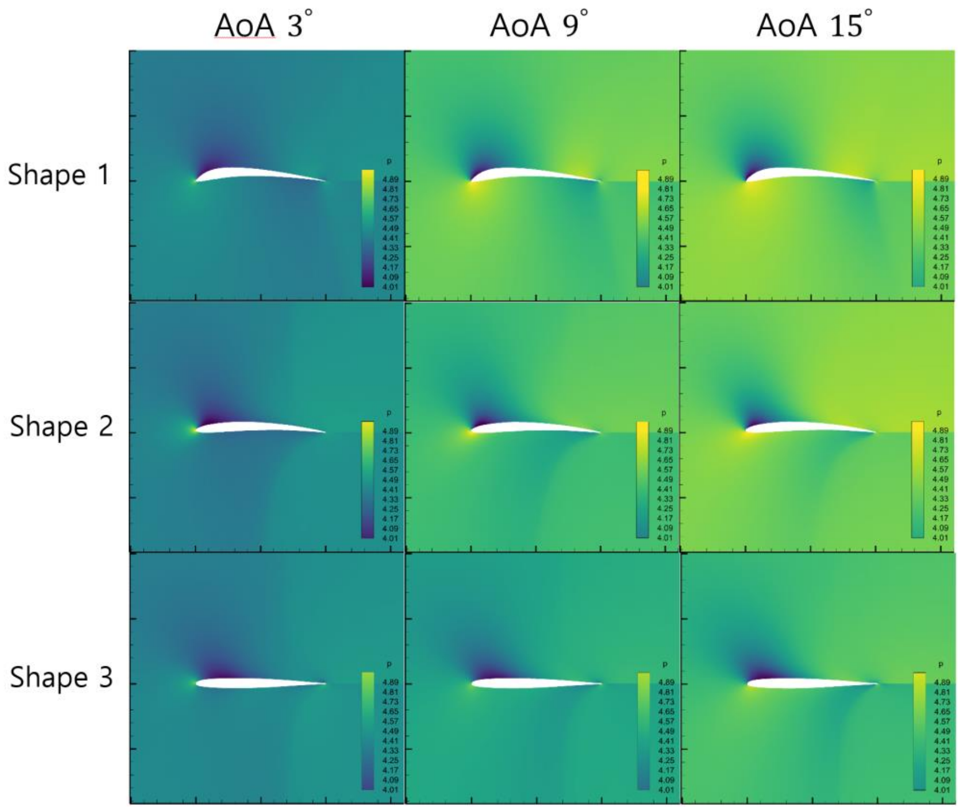


Fig 1. Predicted pressure coefficient contour at various airfoils and AoA

CFD 계산 시간: 180 sec (for 1 case)

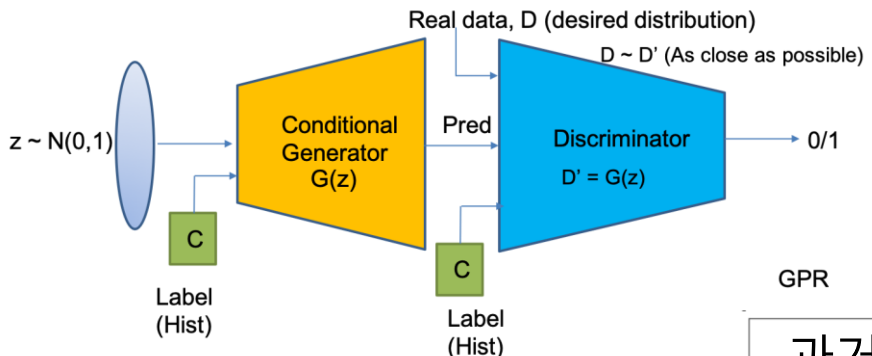
Unet 학습시간 : 0.5 hr (학습조건 따라 상이)

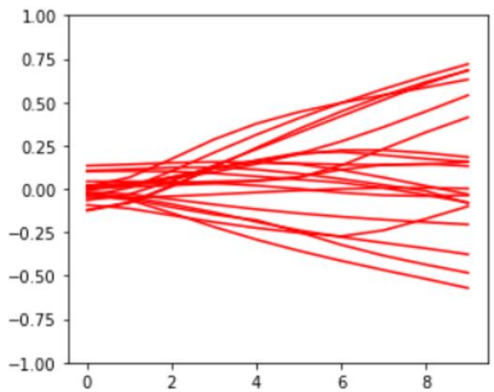
Unet 유동장 예측시간 : 0.73 sec

Mean relative error of test data = 0.28%

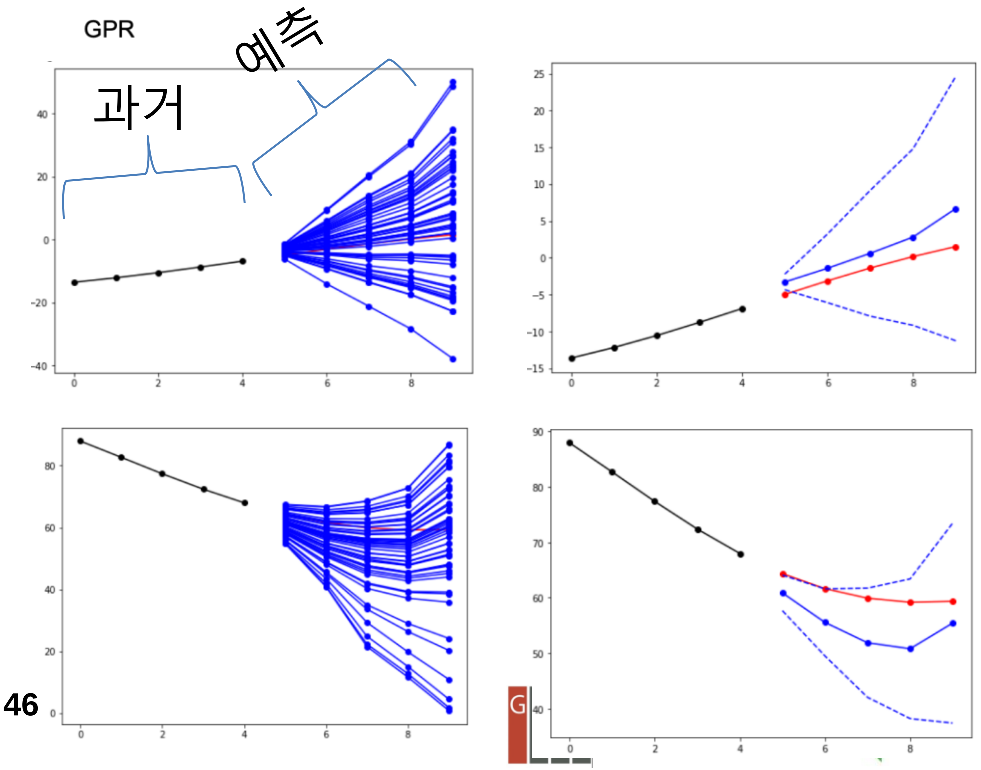
GAN for Design

▣ GAN for Design Candidate Generation, or Inverse Design





Training dataset:
Smooth sinusoidal trajectories



Thank You !