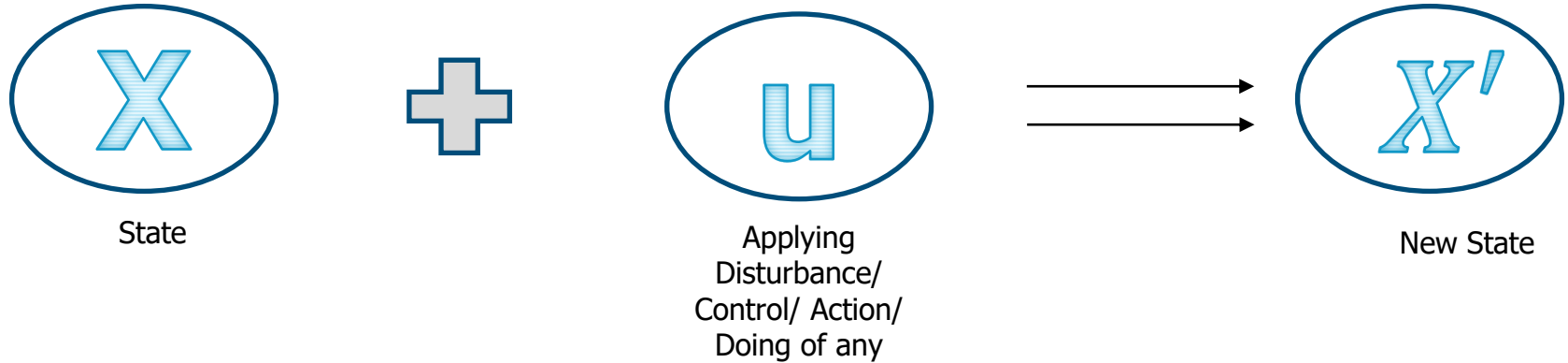




# Deep Koopman Linearization of Nonlinear Dynamical System

Sivaraman Sivaraj

# System and Control



In mathematical expression,

$$x_{k+1} = F(x_k, u)$$

For continuous system,

$$\dot{X} = A.X + B.u \rightarrow \text{integrate it}$$

# Koopman Theory & Benefits:

- The Koopman operator is a linear operator that describes the evolution of scalar observables (i.e., measurement functions of the states) in an infinite dimensional Hilbert space.
- Nonlinear states can be represented as linear in higher dimensional space. The variable which is not part of the dynamics will automatically be eliminated by having zero eigen values.
- Deep Learning Model requires unbiased data which would be larger in size. Koopman Theory models capture the dynamics with lesser amount of data.

# Koopman Operator ( $K$ ):

$$\begin{bmatrix} x_1 \\ x_2 \\ x_3 \end{bmatrix}$$

$$\mathcal{K}_t g = g \circ \mathbf{F}_t$$

$$\mathcal{K}_{\Delta t} g(\mathbf{x}_k) = g(\mathbf{F}_{\Delta t}(\mathbf{x}_k)) = g(\mathbf{x}_{k+1})$$

$$g(\mathbf{x}_{k+1}) = \mathcal{K}_{\Delta t} g(\mathbf{x}_k)$$

- 
- Dynamic Mode Decomposition (DMD)
  - Extended Dynamic Mode Decomposition (eDMD)

*Based on the literature survey, Parsimonious Approach to the model development is limited.*

# Dynamic Mode Decomposition – (*for observation*)

- The Motivation is  $\rightarrow X' = A.X$

- Step 1 : 
$$X = U \Sigma V^T$$

- Step 2 : 
$$X' = A U \Sigma V^T$$

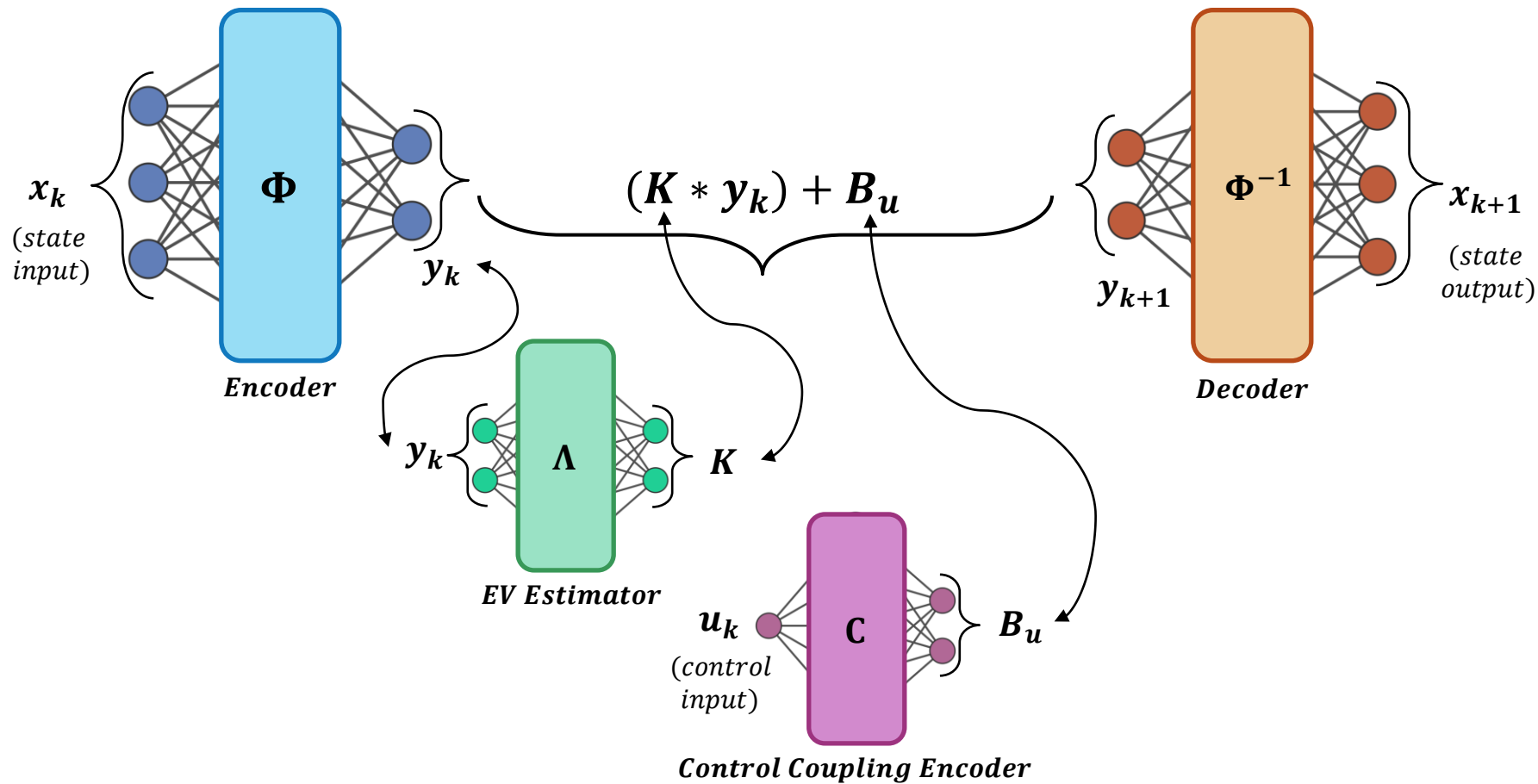
- Step 3 : 
$$\tilde{A} = U^T X' V \Sigma^{-1} = U^T A U$$

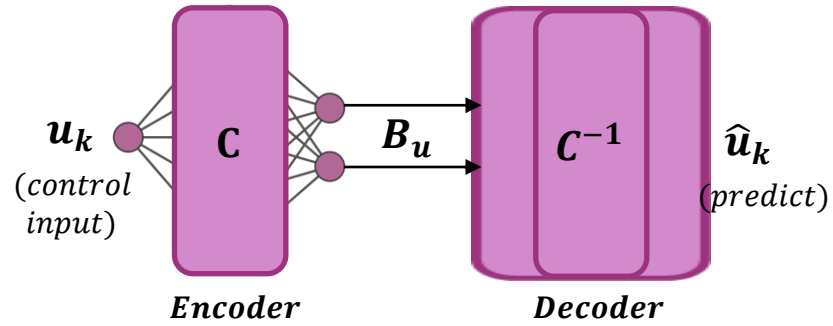
- Step 4 : 
$$\tilde{A}.W = W.\Lambda$$

- Step 5 : 
$$\Phi = X' V \Sigma^{-1} W$$

- Finally dynamical system of coupled spatial temporal modes

- $$\hat{X}(k \Delta t) = \Phi \Lambda^t b_0$$





# Loss Functions :

- Loss Function of Decoder Network:

$$L(\phi^{-1}) = \|x_{k+1} - \phi^{-1}((K * y_k) + B_u)\|$$

- Loss Function of Control Coupling Encoder Network:

$$L(C) = \|\phi(x_{k+1}) - (K * y_k) - B_u\|$$

- Loss Function of Eigen Value Estimator Network:

$$L(\Lambda) = \|\phi(x_{k+1}) - (K * y_k) - B_u\|$$

- Loss Function of Encoder Network:

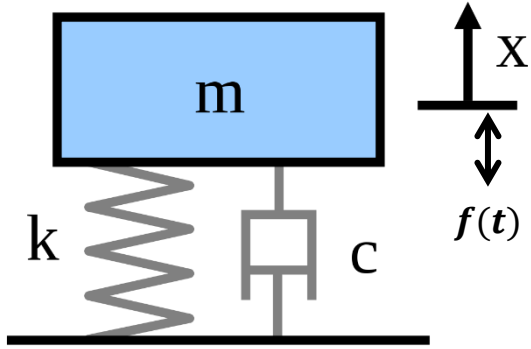
$$L(\phi) = \|x_k - \phi^{-1}(\phi(x_k))\|$$

Back Propagation Order:

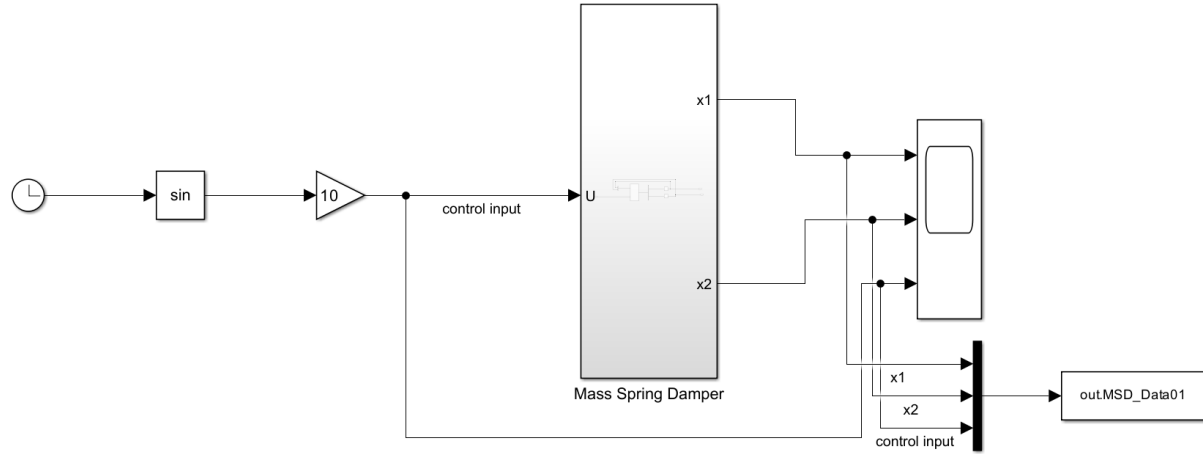
$$\phi^{-1} \rightarrow C \rightarrow \Lambda \rightarrow \phi$$



## Test Case 1 : Mass Spring Damper System



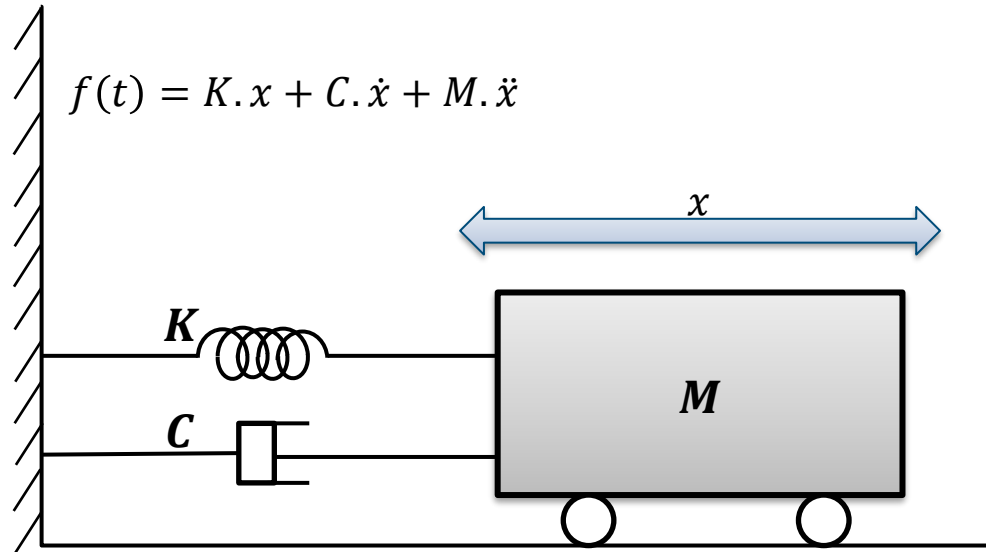
## Pictorial Representation



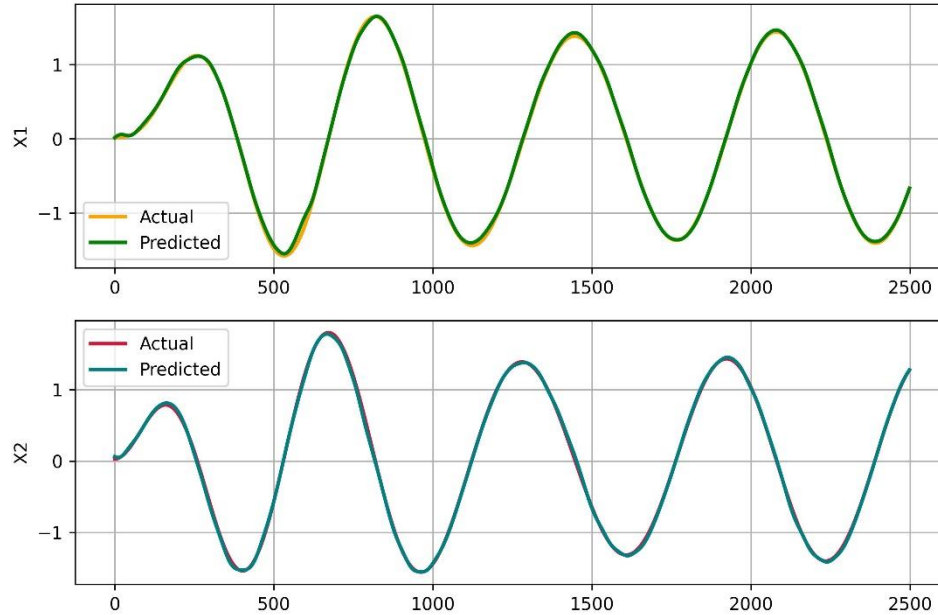
## Simulink setup for Data Generation

$$\begin{bmatrix} \dot{x} \\ \ddot{x} \end{bmatrix} = \begin{bmatrix} \mathbf{0} & \mathbf{1} \\ -\frac{k}{m} & -\frac{c}{m} \end{bmatrix} \cdot \begin{bmatrix} x \\ \dot{x} \end{bmatrix} + \begin{bmatrix} \mathbf{0} \\ \mathbf{1}/m \end{bmatrix} f(t)$$

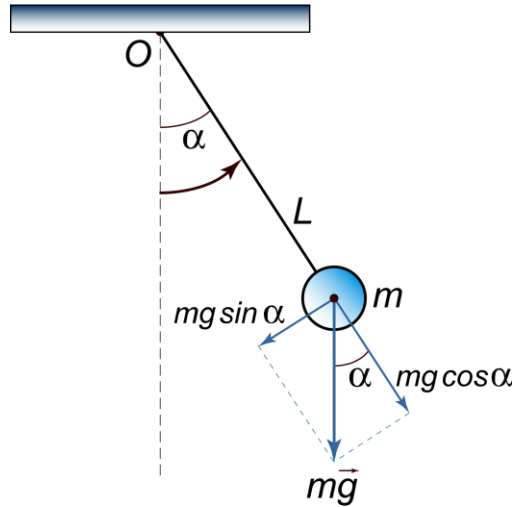
$$\dot{X} = A.X + B.u$$



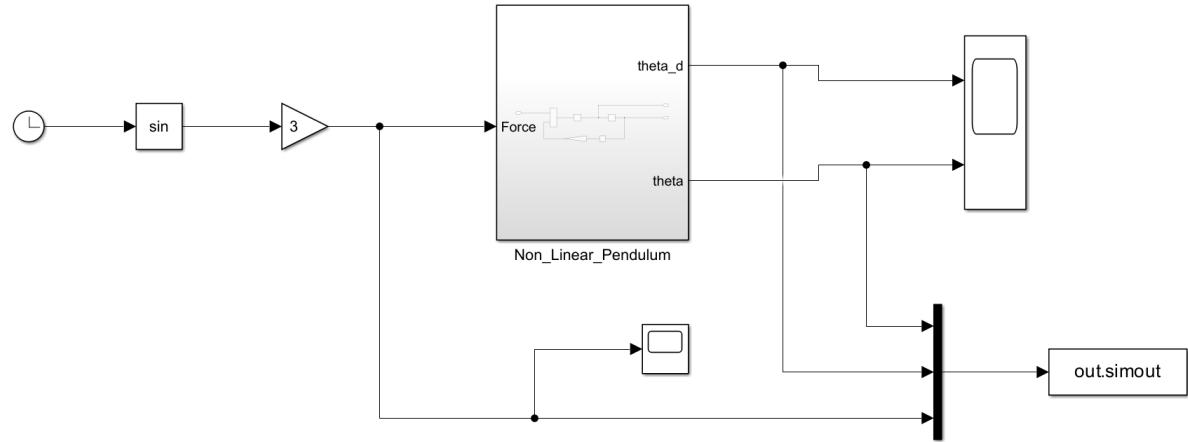
# Test Case 1 : Results



## Test Case 2 : Nonlinear Pendulum



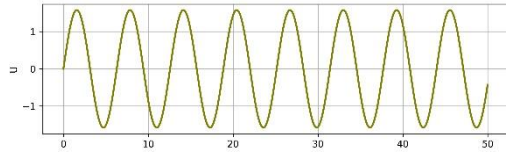
Pictorial Representation



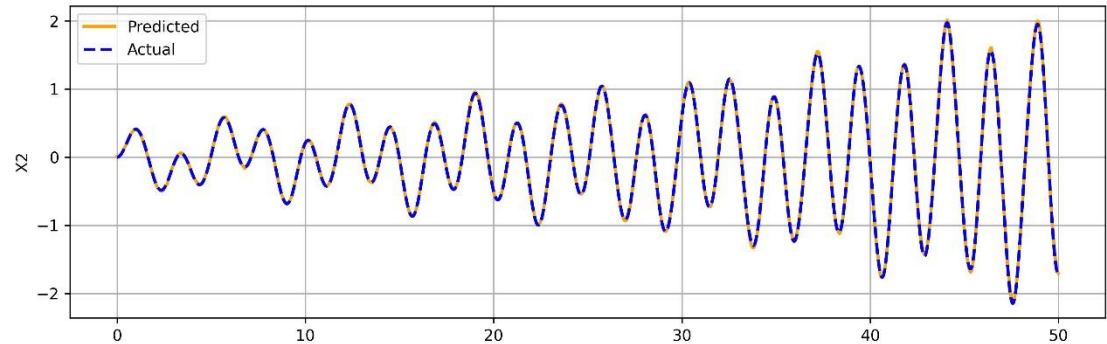
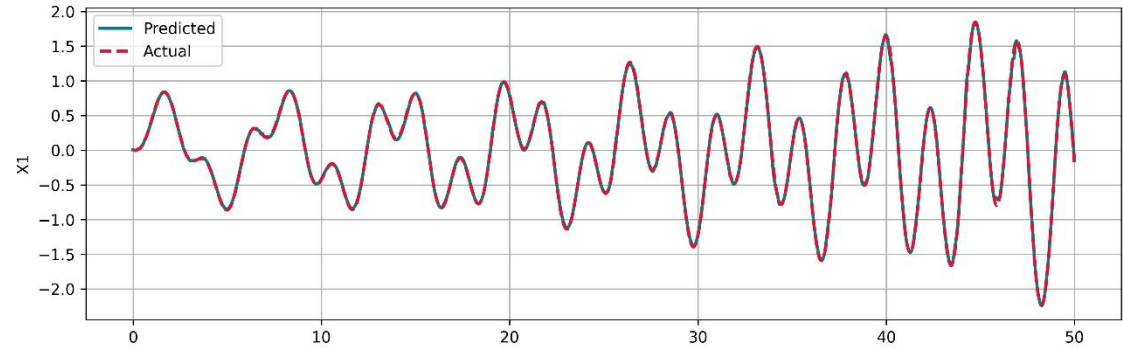
Simulink setup for Data Generation

$$\frac{d^2\alpha}{dt^2} + \frac{g}{L}\sin(\alpha) = f(t) \longrightarrow \dot{X} = f + g \cdot u$$

# Test Case 2 : result

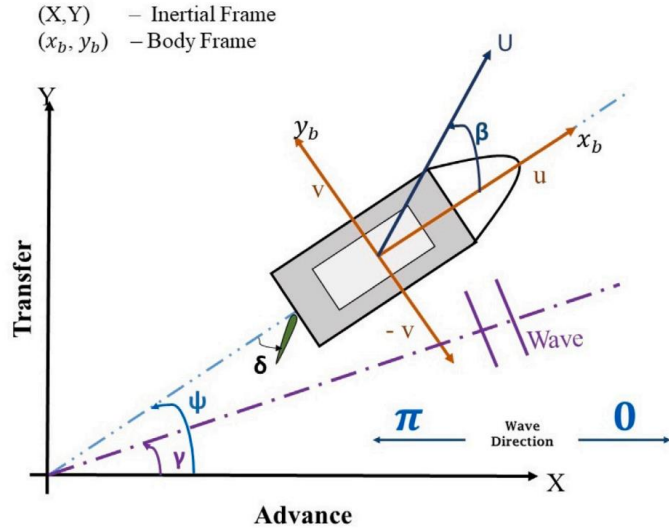


Control Input to the system



State Prediction

# Test Case 4 : Ship Model with Second Order waves



Pictorial Representation

## Dynamical Governing Equation:

$$(m + m_x)\dot{u} - (m + m_y)vr - x_G m r^2 = X_H + X_R + X_P + X_S$$

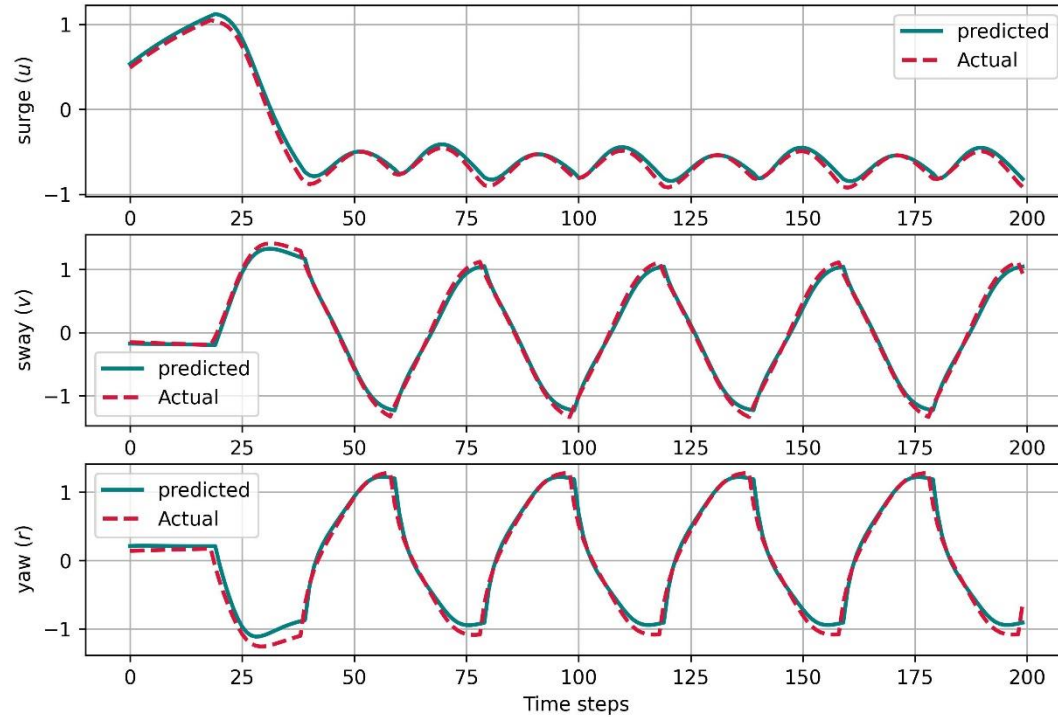
$$(m + m_y)\dot{v} - (m + m_x)ur + x_G m \dot{r} = Y_H + Y_R + Y_S$$

$$(I_z G + x_G^2 m + J_z)\dot{r} + x_G m(\dot{v} + ur) = N_H + N_R + N_S$$

Under Actuated System/ Non-affine System

We can not write such a system in  $\dot{x} = A.x + B.u$  format....!

# Test Case 4 : Result



# Areas Need to Improve & Further Development

- Making the model to work for different sampling time
- Fine tuning of the model
- Testing with various scenarios



# Test Case 3 : Nonlinear Pendulum

