

## ACTIVE VORTEX INDUCED VIBRATION CONTROLLER AND NEURO IDENTIFICATION FOR MARINE RISERS

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### ABSTRACT

In this work, a vortex induced vibration controller within discrete time has been investigated on marine cylinder pipe risers which represented by using nonlinear neuron identification models namely NARX and NAR. Input-output data have been extracted from the experimental rig of vortex induced vibration marine riser. A proposed work in this paper is to create the nonlinear system identification model undergoing for vortex induced vibration of marine riser depends on Neural Network which didn't represented before this time in this application and using PID controller to suppress the vibration. Two nonlinear system identification methods used to represent the models which are: Neural Network based on Nonlinear Auto-Regressive External (Exogenous) Input (NARX) and Neural Network based on Nonlinear Auto-Regressive (NAR). Also, the best model has been chosen based on the lowest value of Mean Square Error (MSE) between actual and predicted response. While, PID controller has been used to suppress the oscillation of pipe cylinder for all models and the comparison of the controller's performance on each model by tuning the controller parameter ( $K_p$ ,  $K_i$  and  $K_d$ ) using heuristic method. Finally, the outcomes show that the NARX model performed better than the NAR model to predict the dynamic response of the system. On the other hand, PID controller has been managed to reduce the pipe cylinder fluctuation for all models specially the NARX model. Using particle swarm optimization (PSO) to improve the stability for marine riser on the parameters of PID controller are planned for future work.

**Keywords:** *Neuro Identification, NARX Model, NAR Model, PID Controller, Vortex Induced Vibration*

### 1. INTRODUCTION

Many researchers consider the phenomenon of Vortex Induced Vibration (VIV) is one of the main problems in the offshore engineering fields because of the elastically dynamic which is mounted on the rigid cylinder to extract the oil from the depths of the sea [1-2]. VIV happens because of the interaction between the body and the vortices shedding behind the structure. Whereas, the vortices behind of the structure create the forces which Working on fluctuation of the cylinder from side to side in one or two directions [3].

The motion of the cylinder from the previous studies can divide into movements: firstly, when the cylinder motion in perpendicular (transverse) to the air or water crossflow generating force called lift force. Secondly, when the cylinder motion in same direction of stream flow (inline) generating force called drag force [4-5]. However,

there are two ways in this field can suppress the oscillation of a pipe cylinder under VIV which is: passive and active vibration control. The first method depends on adding stiffness or mass or changing the sectional area of the structure of the system to raise the natural frequency of the body without the need for external power signal. [6-7]. While, the other method its very used from the first attempt by Baz and Ro (1991) up to now because of this method is cheaper and produce a higher performance more than the passive method and its depend on using sensors and actuators as an external power signal to the system [8].

Nowadays, there are few researchers in this field represented the system behavior by using system identification model to suppress the attenuation of the cylinder during from using controlled methods such as PID and Fuzzy-PID controllers [9-12]. All papers in this field used linear System identification methods (Least Square and Recursive Least Square) to predict the system.

The initial goal in this work to create the model depends on nonlinear system identification methods then using discrete time PID controller.

In this work, the reduction process the effect of VIV on marine risers has been divided into four main sections: firstly, extracting the input-output data of the experimental setup from prior paper. Secondly, using NARX and NAR as a system identification method to predict the dynamic response of the system and validating the results during from MSE technique. Thirdly, study the effectiveness of PID controller discrete time on NARX and NAR models. Recently, discuss the outcomes that obtained from this work.

## 2. EXPERIMENTAL DATA

In this study, the input-output data extracted from previous paper by Shaharuddin and Mat Darus [11-12]. The researchers used the rigid cylinder with flexibly supporting in the crossflow vibration only. Table 1 showing the specification and the parameter values which estimated from experimental test.

Table 1. Obtained Parameters [11-12]

Parameter	Symbol	Value	Unit
Cylinder Diameter	D	50	mm
Cylinder Length	L	1110	mm
Aspect Ratio	L/D	22.2	Dimensionless
Cylinder mass	m	2.95	kg
Mass ratio	m*	1.18	Dimensionless
Natural Frequency in water	fw	1.11	Hz
Damping ratio in water	ζ	0.1007	Dimensionless
System Stiffness	k	265.34	N/m

Input (from accelerometer A) and output (from accelerometer B) data gotten from Shaharuddin and Mat Darus as shown in Figure 1 which included 33000 data for input and output data[11-12].

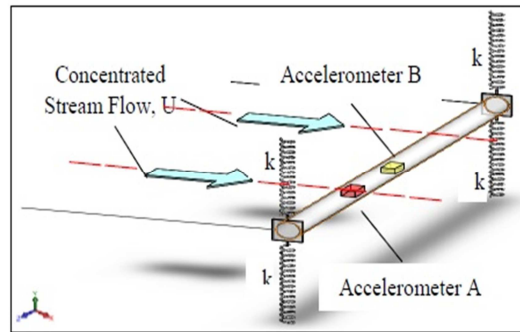


Figure 1. Accelerometer Positions For Detecting And Observing Data Of Experimental Setup Diagram [11-12]

Accelerometer A represents the detected input data for system identification. While, accelerometer B is represents the observed output for system identification. In Figure 2 and 3 shown the relationship between the input and output amplitudes with the time

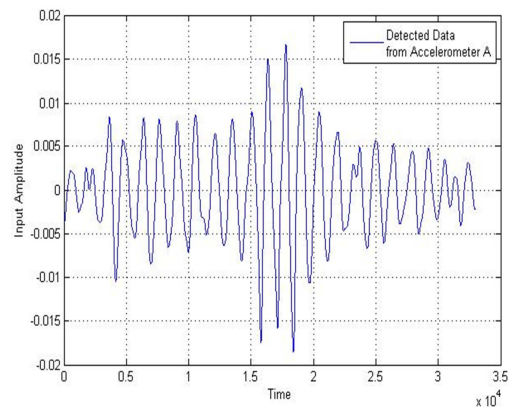


Figure 2. Detected Amplitude With Simple Time Series For Pipe Cylinder

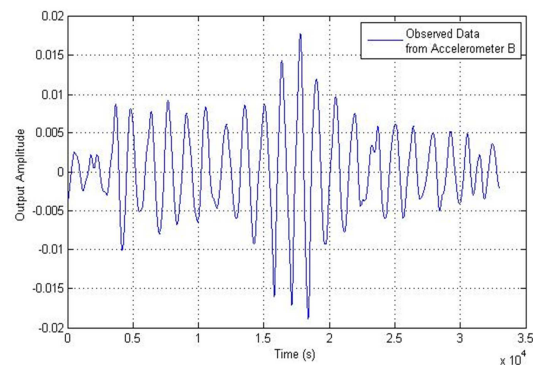


Figure 3. Observed Amplitude With Simple Time Series For Pipe Cylinder

## 3. SYSTEM IDENTIFICATION



In this work, the system identification methods Neural Network time series: Neural Network based on Nonlinear Auto-Regressive External (Exogenous) Input (NARX) and Neural Network based on Nonlinear Auto-Regressive (NAR) used to predict the dynamic response characteristics undergoing vortex induced vibration on the pipe cylinder.

**2.1 Nonlinear Auto-Regressive Model (NAR)**

NAR is one of the methods used to predict the output data for the nonlinear model by using the input or the output data only. The equation of NAR model is [13]:

$$y(t) = f[y(t - 1), \dots, y(t - n_a)] \quad (1)$$

The  $n_a$  represents the previous value of the output.  $f$  is represents the nonlinear function which can be carried out by using intelligent methods such as neural network.

**2.2 Nonlinear Auto-Regressive External Input Model (NRAX)**

NARX model is employed for different purposes such as control and system identification. Also, it is able to forecast the output data in real time. The NARX algorithm can be defined as follows [14]:

$$y(t) = \frac{B(z^{-1})}{A(z^{-1})} u(t) + \frac{\xi(z^{-1})}{A(z^{-1})} \quad (2)$$

where

$$A(z^{-1}) = 1 + a_1 z^{-1} + \dots + a_n z^{-n} \quad (3)$$

$$B(z^{-1}) = b_0 + b_1 z^{-1} + \dots + b_n z^{-(n-1)} \quad (4)$$

After neglecting the noise error and defining the  $B(z^{-1})$  and  $A(z^{-1})$ :

$$y(t) = f[y(t - 1), \dots, y(t - n_a), \dots, u(t - n_k), \dots, u(t - n_k - n_b + 1)] \quad (5)$$

$n_a, n_b$  are represent the previous value of input and output respectively. While, the  $n_k$  represents the input delay. Finally,  $f$  represents the nonlinear function which can be carried out by using intelligent methods such as neural network.

**2.3 Neural Network Time Series**

Neural Network is one of artificial methods which can be used for the nonlinear dynamic system identification. It is consists of a number of neurons arranged in numerous layers. According to Figure 4, Neural Network models include at least three layers which are input, hidden and output layers. The equations can be calculated as follows:

**2.3.1 For hidden layer**

$$v_1 = x_1 w_{11} + x_2 w_{12} + y_1 w_{13} + y_2 w_{14} + b_1 \quad (6)$$

$$v_2 = x_1 w_{21} + x_2 w_{22} + y_1 w_{23} + y_2 w_{24} + b_2 \quad (7)$$

Then

$$f_1 = \frac{1}{1+e^{-v_1}} \quad (8)$$

$$f_2 = \frac{1}{1+e^{-v_2}} \quad (9)$$

where

$x_1, x_2$  are the actual input data of input network.  
 $y_1, y_2$  are the actual output of input network.  
 $w_{11}, w_{12}, w_{13}, w_{14}, w_{21}, w_{22}, w_{23}, w_{24}$  the weights between input and hidden layers.  
 $b_1, b_2$  the bias weights for hidden layer  
 $v_1, v_2$  the summation values for hidden layer  
 $f_1, f_2$  the final values for hidden layer.

**2.3.2 For output layer**

$$v_3 = f_1 w_{31} + f_2 w_{32} + b_3 \quad (10)$$

$$f_3 = \frac{1}{1+e^{-v_3}} \quad (11)$$

where

$w_{31}, w_{32}$  is the weights between the hidden and output layers.  
 $b_3$  is the bias weights for the output layer.  
 $v_3$  is the summation values for the output layer.  
 $f_3$  is the final predicted value for the output layer or neural network process.

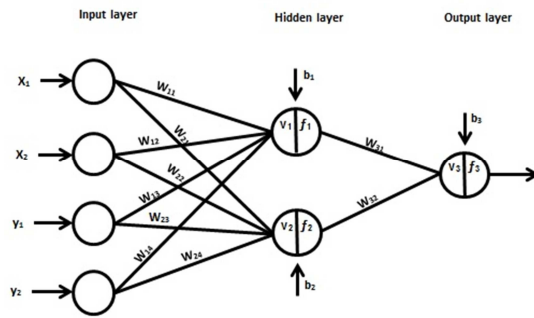


Figure 4. Neural Network Architecture

### 2.4 Validation Technique

The verification process of the result is considered one of the important ways to measure the performance of the mathematical algorithms which used in this paper. Also, check the algorithm effectiveness to ensure that which one is best from the other. In this paper, Mean Square Error method (MSE) used to verify the results obtained in this work. The equation of Mean Square Error is [15]:

$$\varepsilon(t) = \frac{1}{N} \sum_{t=1}^N y(t) - \hat{y}(t)^2 \quad (12)$$

where

$y(t)$  is represents the actual output from experimental setup..

$\hat{y}(t)$  is represents the predicted output which obtained from system identification methods.

The data which used in this paper are divided into two partitions. The first partition is used for testing and the other partition for validating.

### 4. SYSEM IDENTIFICATION SIMULATION DESIGN

Depends on the Neural Network times series in MATLAB toolbox, number of neurons and number of delay considered the important variables to generate the nonlinear model for NARX and NAR models after specifying number of training, validating and testing data as shown in figure 5. The simulation procedure has been divided into three parts: firstly, 70% of data used for training, 15% of fata used for validating and 15% of data used for testing. Secondly, specify the number of neurons and delay with variant cases and finally create the model depends on the MSE values and find the best model as shown in figure 6.

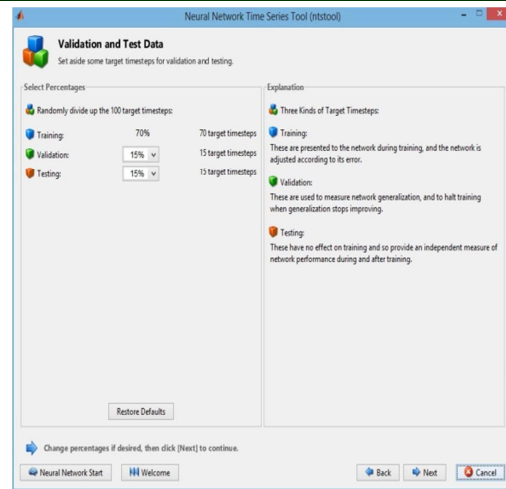
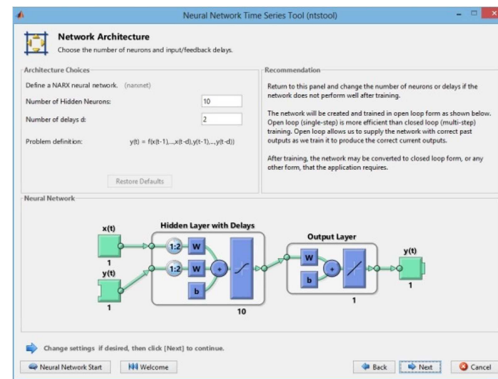
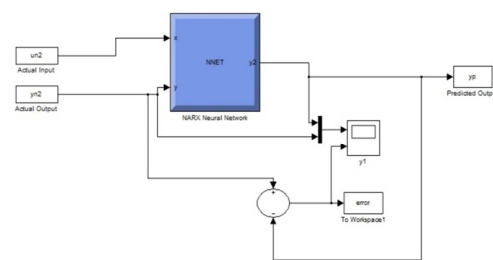


Figure 5: Specify The Percentage Values For Training, Validating And Testing Data



(a)



(b)

Figure 6: Specify The Number of Neurons And Delay (a) and Block Scheme For System Identification Models

### 5. PID CONTROLLER

One of the conventional controllers used in the control field of all disciplines around the world. In this work, PID controller employed to suppress the movement of the pipe cylinder for marine risers under vortex emerged vibration to calculate the

value of the error between the output measured and the desired set point under disturbance load as shown in Figure 7. The process required using a heuristic method to find and tunes the PID parameters ( $K_I$ ,  $K_P$  and  $K_D$ ). Also, this method depended on mean square error (MSE) technique to validate the gain values of the PID parameters under disturbed load which it's included three steps [16]: firstly, calculating the last proportional gain value ( $K_P$ ) by assuming different values until reaching this gain to the lower MSE of the system when being the integral and derivative gain values equal to zero. Secondly, accounting for the last integral gain value ( $K_I$ ) by assuming different values until reaching this gain to the lower MSE of the system when being the proportional gain equal to the last value for the first step and the derivative value equal to zero. Finally, calculating the last derivative gain value ( $K_D$ ) by assuming the different values for this gain until reaching it to the lower MSE of the system when being the proportional and the derivative gain values equal to the last value of the first and second steps respectively. Figure 8 shown the block diagram for marine risers system which it's undergoes in the vortex induced vibration as a distributed load with PID controller discrete time.

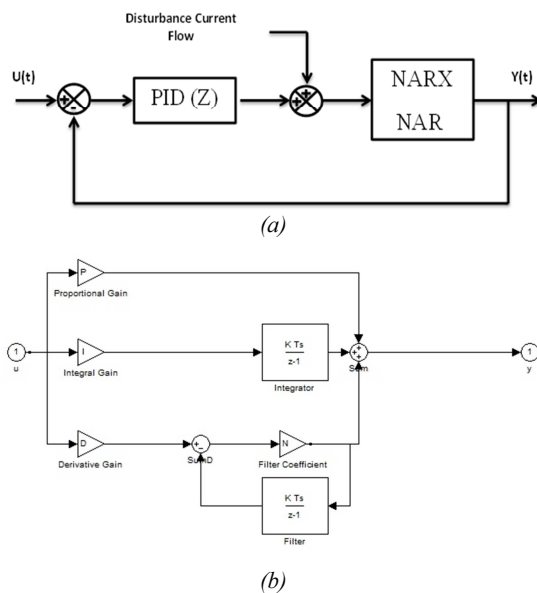


Figure 7: The Block Scheme For Controller And System Identification

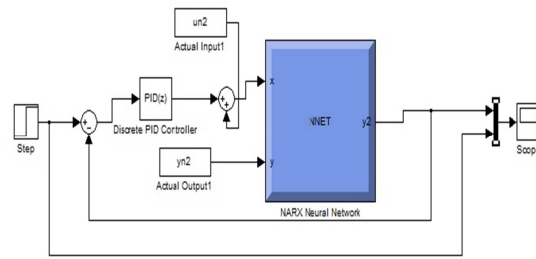


Figure 5. The Block Scheme for Controller And System Identification

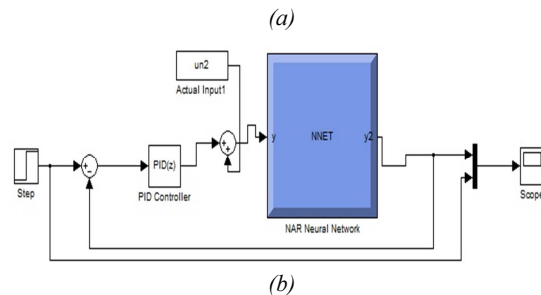


Figure 8: The Block Scheme for Controller With (A) System Identification (NARX) and (B) System Identification (NAR)

## 6. RESULTS AND DISCUSSIONS

### 6.1 System Identification For NARX Model

Neural Network based on Nonlinear Auto-Regressive external input model (NARX) has been employed to predict the dynamic response of the system. In this method, 33000 data used as an input and output data which extracted from the experimental setup for prior paper and it's distributed into two inputs and one output. Whereas, all data separated into three portions: firstly, 32100 data. Secondly, 4950 used to validate the system and last part utilized 4950 data for testing. Also, in this paper used different values for the number of neurons (NE) which ranged between 1 to 11 neurons for default number of delays 2 to find the lower MSE. Then, the best result from pervious process fixed and used for different number of delays until finding the lower MSE which ranged between 1 to 11 values. Based on the Table 2, the lowest MSE founded at neurons (NE) 8 is  $1.2714 \times 10^{-9}$  when the numbers of delay has been fixed at 2. While, Table 3 shown that the lowest MSE founded the number of delay 2 is  $1.2714 \times 10^{-9}$  when the number of neurons has been fixed at 8. That's means that the best representation for the NARX model to describe the dynamic response when being the number of neurons and the numbers of delay equal 8 and 2 respectively. Figure 9 and 10 showed the best representation for NARX model at

NE equal 8 and number of delay 2 for amplitude and error.

Table 2 Mean Square Error for NARX Model at Number of Delay 2

NE	MSE for training	MSE validate d	MSE tested	MSE Overall
1	$7.06994 \times 10^{-7}$	$7.03911 \times 10^{-7}$	$7.30382 \times 10^{-7}$	$7.1048 \times 10^{-7}$
2	$1.51825 \times 10^{-7}$	$1.46421 \times 10^{-7}$	$1.63488 \times 10^{-7}$	$1.5353 \times 10^{-7}$
3	$2.51148 \times 10^{-9}$	$2.53456 \times 10^{-9}$	$2.49492 \times 10^{-9}$	$3.2278 \times 10^{-9}$
4	$2.25323 \times 10^{-8}$	$2.10880 \times 10^{-8}$	$2.24574 \times 10^{-8}$	$2.2795 \times 10^{-8}$
5	$1.90786 \times 10^{-9}$	$1.88947 \times 10^{-9}$	$1.91908 \times 10^{-9}$	$2.2781 \times 10^{-9}$
6	$2.33170 \times 10^{-8}$	$2.42179 \times 10^{-8}$	$2.39115 \times 10^{-8}$	$2.4056 \times 10^{-8}$
7	$8.42986 \times 10^{-8}$	$8.52992 \times 10^{-8}$	$8.58115 \times 10^{-8}$	$8.5672 \times 10^{-8}$
8	$4.7337 \times 10^{-10}$	$4.7219 \times 10^{-10}$	$4.7699 \times 10^{-10}$	$1.2714 \times 10^{-9}$
9	$3.27642 \times 10^{-9}$	$3.31040 \times 10^{-9}$	$3.41665 \times 10^{-9}$	$4.0278 \times 10^{-9}$
10	$6.28938 \times 10^{-9}$	$6.58235 \times 10^{-9}$	$6.65887 \times 10^{-9}$	$6.7772 \times 10^{-9}$
11	$1.60514 \times 10^{-8}$	$1.62700 \times 10^{-8}$	$1.75777 \times 10^{-8}$	$1.6682 \times 10^{-8}$

Table 3 Mean Square Error for NARX Model at Number of Hidden Neuron 8

No. of Delay	MSE for training	MSE validate d	MSE tested	MSE Overall
1	$1.2692 \times 10^{-8}$	$1.2709 \times 10^{-8}$	$1.3011 \times 10^{-8}$	$1.3078 \times 10^{-8}$
2	$4.7337 \times 10^{-10}$	$4.7219 \times 10^{-10}$	$4.7700 \times 10^{-10}$	$1.2714 \times 10^{-9}$
3	$2.3379 \times 10^{-10}$	$2.2933 \times 10^{-10}$	$2.3540 \times 10^{-10}$	$1.3273 \times 10^{-9}$
4	$6.0016 \times 10^{-9}$	$6.0448 \times 10^{-7}$	$5.9680 \times 10^{-7}$	$6.4521 \times 10^{-9}$
5	$1.8549 \times 10^{-8}$	$1.8502 \times 10^{-8}$	$1.8931 \times 10^{-8}$	$1.9537 \times 10^{-8}$
6	$3.0966 \times 10^{-8}$	$3.1253 \times 10^{-8}$	$1.0954 \times 10^{-8}$	$3.2182 \times 10^{-8}$
7	$3.3785 \times 10^{-8}$	$3.6127 \times 10^{-8}$	$3.4293 \times 10^{-8}$	$3.4956 \times 10^{-8}$
8	$1.3636 \times 10^{-9}$	$1.3966 \times 10^{-9}$	$1.3686 \times 10^{-9}$	$2.8229 \times 10^{-9}$
9	$2.0855 \times 10^{-9}$	$2.0098 \times 10^{-9}$	$1.9893 \times 10^{-9}$	$3.7473 \times 10^{-9}$
10	$2.7858 \times 10^{-9}$	$2.7113 \times 10^{-9}$	$2.8606 \times 10^{-9}$	$2.8790 \times 10^{-9}$
11	$7.7023 \times 10^{-9}$	$7.7061 \times 10^{-9}$	$8.0669 \times 10^{-9}$	$8.9183 \times 10^{-9}$

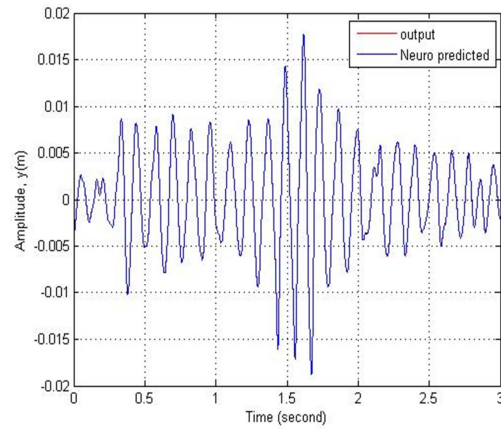


Figure 9: The Amplitude Of Actual And Predicted Output Depends On NARX

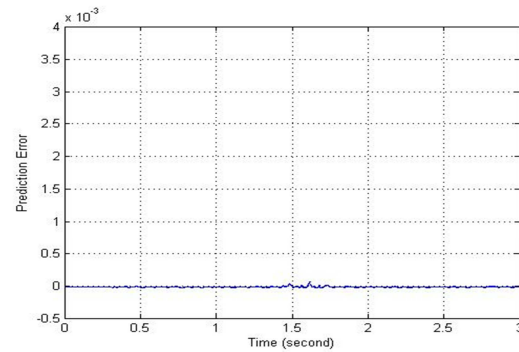


Figure 10: The Error Of The Predicted Output Depends On NARX

## 6.2 System Identification For NAR model

Neural Network based on Nonlinear Auto-Regressive model (NAR) has been utilized to get the dynamic response of the system. In this method, the equal numbers of data used for input, output, training, validating and testing for NARX method. Also, the same procedure of NARX model for numbers of neuron and number of delay used in NAR model. Based on the Table 4, the lowest MSE founded in neurons (NE) 6 is  $6.6542 \times 10^{-9}$  when the numbers of delays have been fixed at 2. While, Table 5 shown that the lowest MSE founded the number of delays 4 is  $2.8452 \times 10^{-9}$  when the number of neurons has been fixed at 6. That's means that the best representation for the NAR model to describe the dynamic response when being the number of neurons and the numbers of delay equal 6 and 4 respectively. Figure 11 and 12 showed the best representation for NAR model for NE equal 6 and number of delay 4 for amplitude and error.

Table 4 Mean Square Error for NAR Model at Number of Delay 2

NE	MSE for training	MSE validate d	MSE tested	MSE Overall
1	1.21865x10 <sup>-8</sup>	1.23348x10 <sup>-8</sup>	1.47379x10 <sup>-8</sup>	1.3618x10 <sup>-8</sup>
2	4.69192x10 <sup>-7</sup>	4.44050x10 <sup>-7</sup>	5.13385x10 <sup>-7</sup>	4.7309x10 <sup>-7</sup>
3	6.160202x10 <sup>-8</sup>	6.42999x10 <sup>-8</sup>	6.11500x10 <sup>-8</sup>	6.2567x10 <sup>-8</sup>
4	2.95893x10 <sup>-7</sup>	2.89721x10 <sup>-7</sup>	3.12913x10 <sup>-7</sup>	2.9778x10 <sup>-7</sup>
5	1.01116x10 <sup>-8</sup>	1.02313x10 <sup>-8</sup>	1.00981x10 <sup>-8</sup>	1.0532x10 <sup>-8</sup>
6	5.82502x10 <sup>-9</sup>	5.97741x10 <sup>-9</sup>	5.76880x10 <sup>-9</sup>	6.6542x10 <sup>-9</sup>
7	9.52759x10 <sup>-8</sup>	8.19346x10 <sup>-8</sup>	1.00706x10 <sup>-7</sup>	9.4854x10 <sup>-8</sup>
8	7.40069x10 <sup>-9</sup>	6.37130x10 <sup>-9</sup>	6.98316x10 <sup>-9</sup>	7.7572x10 <sup>-9</sup>
9	2.54389x10 <sup>-8</sup>	2.79919x10 <sup>-8</sup>	2.74169x10 <sup>-8</sup>	2.9366x10 <sup>-8</sup>
10	1.45673x10 <sup>-8</sup>	1.48914x10 <sup>-8</sup>	1.48435x10 <sup>-8</sup>	1.6209x10 <sup>-8</sup>
11	9.78359x10 <sup>-8</sup>	8.76832x10 <sup>-8</sup>	9.03277x10 <sup>-8</sup>	9.5864x10 <sup>-8</sup>

Table 5 Mean Square Error for NAR Model at Number of Hidden Neuron 6

No. of Delay	MSE for training	MSE validate d	MSE tested	MSE Overall
1	1.43914x10 <sup>-7</sup>	3.98960x10 <sup>-7</sup>	3.99911x10 <sup>-7</sup>	4.0290x10 <sup>-7</sup>
2	5.82502x10 <sup>-9</sup>	5.97741x10 <sup>-9</sup>	5.76880x10 <sup>-9</sup>	6.6542x10 <sup>-9</sup>
3	3.47933x10 <sup>-9</sup>	3.43426x10 <sup>-9</sup>	3.52902x10 <sup>-9</sup>	4.1027x10 <sup>-9</sup>
4	9.78777x10 <sup>-10</sup>	9.78197x10 <sup>-10</sup>	9.87599x10 <sup>-10</sup>	2.8452x10 <sup>-9</sup>
5	1.04383x10 <sup>-8</sup>	1.03251x10 <sup>-8</sup>	1.04343x10 <sup>-8</sup>	1.1098x10 <sup>-8</sup>
6	5.04420x10 <sup>-9</sup>	4.97154x10 <sup>-9</sup>	4.94863x10 <sup>-9</sup>	6.3538x10 <sup>-9</sup>
7	4.52312x10 <sup>-8</sup>	4.65865x10 <sup>-8</sup>	4.73918x10 <sup>-8</sup>	4.7095x10 <sup>-8</sup>
8	7.65045x10 <sup>-9</sup>	7.90956x10 <sup>-9</sup>	7.81632x10 <sup>-9</sup>	8.8763x10 <sup>-9</sup>
9	1.84328x10 <sup>-9</sup>	1.87072x10 <sup>-9</sup>	1.81564x10 <sup>-9</sup>	3.0986x10 <sup>-9</sup>
10	7.23659x10 <sup>-8</sup>	7.55279x10 <sup>-8</sup>	7.30517x10 <sup>-8</sup>	7.3678x10 <sup>-8</sup>
11	1.37098x10 <sup>-8</sup>	1.21062x10 <sup>-8</sup>	1.32999x10 <sup>-8</sup>	1.4201x10 <sup>-8</sup>

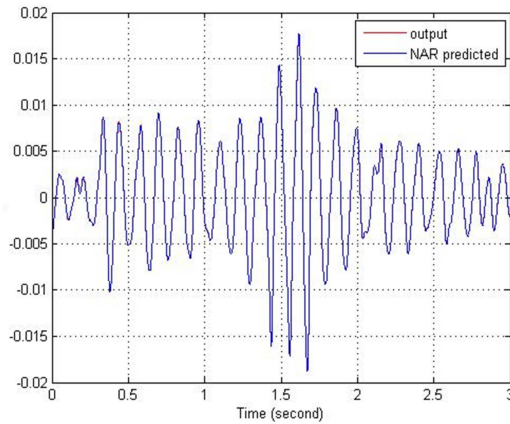


Figure 11: The Amplitude Of Actual And Predicted Output Depends On NAR

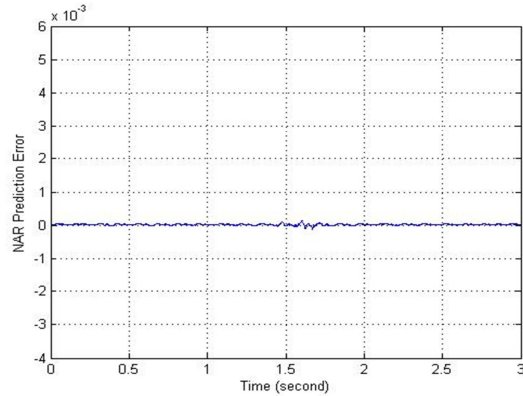


Figure 12: The Error Of The Predicted Output Depends On NAR

### 6.3 PID Controller for NARX and NAR Models

PID controller has been utilized to reduce the pipe cylinder oscillation caused by VIV which is represented by using NARX and NAR system identification models after comparison of the results between system identification models. The PID parameters have been set during of the heuristic method which is consisted to find P gain value at lowest MSE, then finding PI gain values at lowest MSE and finally finding PID gain values at the Lowest MSE. Details of the results divided into two parts: firstly, Table 6 shown the outcomes for NARX which recorded the best magnitude for  $K_p = -5$  at lowest MSE equal  $6.147 \times 10^{-6}$ . Also, the best magnitude for  $K_I = -2.5$  at lowest MSE equal  $3.832 \times 10^{-10}$ . While the best magnitude for  $K_D = -0.2$  at lowest MSE equal  $3.669 \times 10^{-10}$ . According to Figure 13 and 14, the results shown that the PID controller has been succeeded to suppress the effect

of VIV comparison with the system performance without controller.

Table 6 PID parameter setting for NARX model by using MSE

K <sub>p</sub>	MSE	K <sub>i</sub>	MSE	K <sub>d</sub>	MSE
1	8.519x10 <sup>-4</sup>	1	9.15x10 <sup>-4</sup>	1	4.527x10 <sup>-4</sup>
-1	3.353x10 <sup>-4</sup>	-1	1.009x10 <sup>-9</sup>	0	3.832x10 <sup>-10</sup>
-2	4.027x10 <sup>-5</sup>	-1.5	5.633x10 <sup>-10</sup>	-0.1	3.714x10 <sup>-10</sup>
-4	6.718x10 <sup>-6</sup>	-2	4.211x10 <sup>-10</sup>	-0.15	3.682x10 <sup>-10</sup>
-5	6.147x10 <sup>-6</sup>	-2.5	3.832x10 <sup>-10</sup>	-0.2	3.669x10 <sup>-10</sup>
-6	5.687x10 <sup>-4</sup>	-3	4.353x10 <sup>-10</sup>	-0.25	3.677x10 <sup>-10</sup>

1.4020x10<sup>-8</sup>. While the best magnitude for K<sub>D</sub> = 0.03 at lowest MSE equal 1.3584x10<sup>-8</sup>. According to Figure 15 and 16, the results shown that the PID controller has been succeeded to suppress the effect of VIV comparison with the system performance without controller.

Table 7 PID parameter setting for NAR model by using MSE

K <sub>p</sub>	MSE	K <sub>i</sub>	MSE	K <sub>d</sub>	MSE
-0.1	3.3027x10 <sup>-5</sup>	-0.1	2.3957x10 <sup>-4</sup>	-0.1	2.0069x10 <sup>-4</sup>
0.1	2.161x10 <sup>-5</sup>	0	1.9047x10 <sup>-5</sup>	0	1.4020x10 <sup>-8</sup>
0.2	2.0308x10 <sup>-5</sup>	0.1	8.0051x10 <sup>-8</sup>	0.01	1.3754x10 <sup>-8</sup>
0.23	1.9339x10 <sup>-5</sup>	0.2	2.3745x10 <sup>-8</sup>	0.02	1.3611x10 <sup>-8</sup>
0.24	1.9047x10 <sup>-5</sup>	0.3	1.4020x10 <sup>-8</sup>	0.03	1.3584x10 <sup>-8</sup>
0.25	1.9061x10 <sup>-5</sup>	0.4	1.4519x10 <sup>-8</sup>	0.04	1.3697x10 <sup>-8</sup>

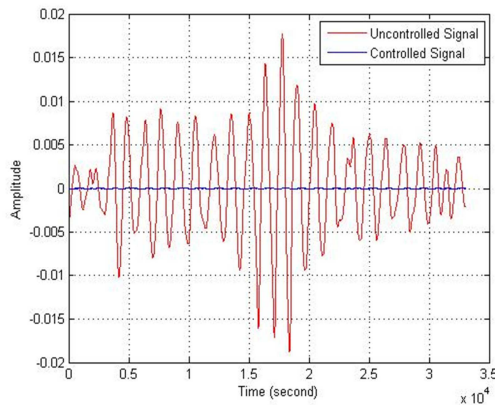


Figure 13: NARX Model Performances With And Without PID Controller.

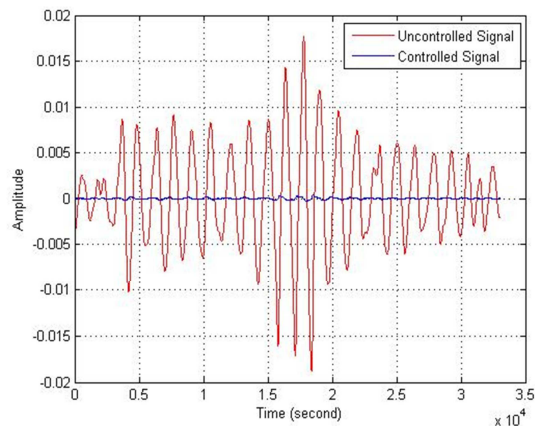


Figure 15: NAR Model Performance With And Without PID Controller.

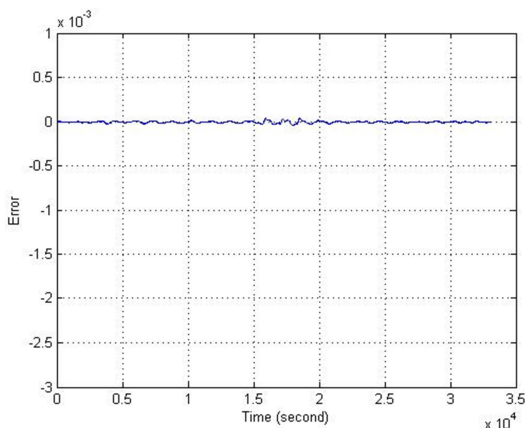


Figure 14: Error Between The Setting Reference Point And Desired Amplitude.

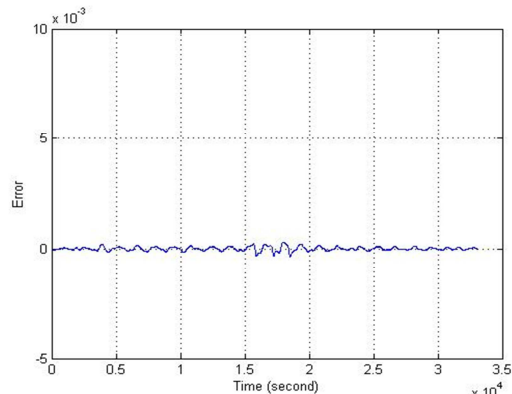


Figure 16: Error between the setting reference point and desired amplitude.

Secondly, Table 7 shown the outcomes for NAR which recorded the best magnitude for K<sub>p</sub> = 0.24 at lowest MSE equal 1.9047x10<sup>-5</sup>. Also, the best magnitude for K<sub>i</sub> = 0.3 at lowest MSE equal



According to all results above, the PID controller has ability to suppress the effect of VIV. But, the performance of PID controller for NARX model was better the NAR model where it's recorded the MSE equal  $3.669 \times 10^{-10}$  while the MSE for PID controller on NAR model equal  $1.3584 \times 10^{-8}$ . That's mean that controller was able to reduce the vibrations around 97 % from the original case without using the controller for NAR model. From the other hand, the controller on the NARX model was able to reduce the vibrations for the marine riser around 99% from the original case without using the controller. Figure 17 has shown the performance of PID controller on NARX model against NAR model.

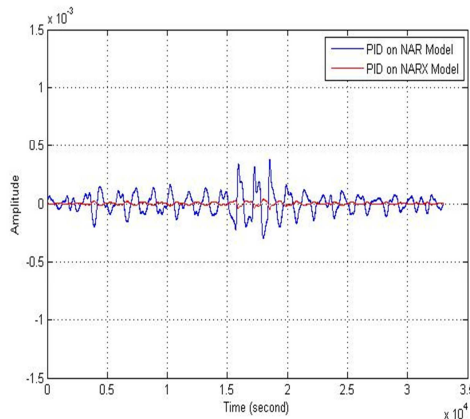


Figure 17: PID Controller Performance On NARX And NAR Models.

## CONCLUSION

The performance of PID controller for NARX and NAR system identification models for oscillating pipe riser under vortex induced vibration has been investigated in this paper. The input-output data extracted from the experimental setup for priority research. NARX and NAR models employed to represent the dynamic response of the system after comparing the results for different number of hidden neurons and numbers of delay by using MSE technique. The PID controller proved to be effective to decrease the effect of vortex induced vibration of a pipe cylinder under disturbance load for all models. But the PID performance on NARX model was better than the NAR model which recorded the lowest MSE  $3.669 \times 10^{-10}$  while the MSE for PID controller for NAR model equal  $1.3584 \times 10^{-8}$ .

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## REFERENCES:

- [1] C. H. K. Williamson and R. Govardhan, "Vortex-Induced Vibrations," *Annu. Rev. Fluid Mech.*, vol. 36, no. 1, 2004, pp. 413–455.
- [2] T. L. Morse and C. H. K. Williamson, "Prediction of Vortex-Induced Vibration Response by Employing Controlled Motion," *J. Fluid Mech.*, vol. 634, 2009, pp. 5-39.
- [3] B. V. E. How, S. S. Ge, and Y. S. Choo, "Active Control of Flexible Marine Risers," *J. Sound Vib.*, vol. 320, no. 4–5, 2009, pp. 758–776.
- [4] F. Flemming and C. H. K. Williamson, "Vortex-Induced Vibrations of A Pivoted Cylinder," *J. Fluid Mech.*, vol. 522, 2005, pp. 215–252.
- [5] L. Cheng, Y. Zhou, and M. M. Zhang, "Perturbed Interaction Between Vortex Shedding and Induced Vibration," *J. Fluids Struct.*, vol. 17, no. 7, 2003, pp. 887–901.
- [6] O. Streets and A. R. E. Formed, "Feedback Control of Vortex Shedding From a Circular Cylinder by Rotational," *J. of Fluid and Structure*, VI. 15, 2001, pp. 23–37.
- [7] L. Cheng, Y. Zhou, and M. M. Zhang, "Controlled Vortex-Induced Vibration on A Fix-Supported Flexible Cylinder in Cross-Flow," *J. Sound Vib.*, vol. 292, no. 1–2, 2006, pp. 279–299.
- [8] J. Ro, "Active Control of Flow-Induced Using Feedback Vibrations Velocity Of A Flexible Cylinder Direct," *J. Sound Vib.*, vol. 146, no. 1, 1991, pp. 33–45.
- [9] N. M. R. Shaharuddin and I. Z. Mat Darus, "Active Vibration Control of Marine Riser," *2012 IEEE Conf. Control. Syst. Ind. Informatics*, Sep. 2012, pp. 114–119.
- [10] C.-M. Chang and B. F. Spencer, "Hybrid System Identification For High-Performance Structural Control," *Eng. Struct.*, vol. 56, 2013, pp. 443–456.
- [11] N. M. R. Shaharuddin and I. Z. M. Darus, "Fuzzy-PID Control of Transverse Vibrating Pipe Due to Vortex Induced Vibration," *UKSim 15th Int. Conf. Comput. Model. Simul.*, Apr. 2013, pp. 21–26.



- [12] N. M. R. Shaharuddin and I. Z. Mat Darus, "System Identification of Flexibly Mounted Cylindrical Pipe Due to Vortex Induced Vibration," *IEEE Symp. Comput. Informatics*, Apr. 2013, pp. 30–34.
- [13] V. L. Syrmos, "Nonlinear System Identification And Fault Detection Using Hierarchical Clustering Analysis and Local Linear Models," *Mediterr. Conf. Control Autom.*, Jun. 2007, pp. 1–6.
- [14] H. Peng, T. Ozaki, Y. Toyoda, H. Shioya, K. Nakano, V. Haggan-Ozaki, and M. Mori, "RBF-ARX Model-Based Nonlinear System Modeling And Predictive Control With Application to a Nox Decomposition Process," *Control Eng. Pract.*, vol. 12, no. 2, 2004, pp. 191–203.
- [15] A. R. Tavakolpour, I. Z. Mat Darus, O. Tokhi, and M. Mailah, "Genetic Algorithm-Based Identification of Transfer Function Parameters for a Rectangular Flexible Plate System," *Eng. Appl. Artif. Intell.*, vol. 23, no. 8, 2010, pp. 1388–1397.
- [16] M. A. Fadil, I. Z. M. Darus, M. S. Ammoo, and J. Bahru, "Iterative Learning Auto-tuned PID Controller for Micro-Unmanned Air Vehicle," *Conf. on Instrumentation, Measurement, Circuits and Systems*, Apr. 2013, pp. 153–160.