Grey Wolf Optimization For Intelligent Parametric Modeling Of Gradient Flexible Plate Structure

M.H. Hassan[1], A. Jamali[1*], R. Lidyana[1], M.S.Z.M Suffian[1], M.S Hadi[2], and I.Z. Mat Darus[3]

[1] *Department of Mechanical Engineering, Faculty of Engineering, Universiti Malaysia Sarawak, 94000 Sarawak, Malaysia.*
[2] *School of Mechanical Engineering, College of Engineering, Universiti Teknologi MARA, 40450, Shah Alam, Selangor.*
[3] *School of Mechanical Engineering, Faculty of Engineering, Universiti Teknologi Malaysia, 81310, Skudai, Johor Bahru.*
[*] *Corresponding author. E-mail: annisajamali@gmail.com*

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This paper presents the dynamic modeling of the gradient flexible plate system using System Identification method based on autoregressive with exogenous input model structure and estimated by Grey Wolf Optimization. The experimental rig of the gradient flexible plate was integrated with the data acquisition and instrumentation to obtain input-output vibration data. The performances of developed models were validated through one step ahead prediction, mean squared error, and correlation tests. The model was verified using the pole-zero diagram to confirm its stability for the controller development. Results indicated that the optimum model to represent the dynamic system of gradient flexible plate was achieved by model order 4 with the mean squared error of 8.0496×10^{-6}. The correlation results proved that the model was unbiased, and falls within the 95% confidence level. Likewise, the model was found to be stable as all the poles of transfer function were within the unit circle. Therefore, the identified model can be confidently used for the controller development to suppress undesirable vibration in the gradient flexible plate structure.

Keywords: Gradient flexible plate, grey wolf optimization, parametric modeling

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1. Introduction

Flexible plate structures have sparked a lot of interest in engineering fields such as automotive, aviation, and shipping, as well as material handling at airport luggage, industrial businesses, and supermarkets. Many flexible structures in real-world applications are formed at various orientations for instance the aircraft wall [1], car frame and engine elements [2], the conveyor system in food industries [3], and ship body [4]. This is in line with the industrial trend of reducing the weight of mechanical structures to improve system performance while lowering production costs. However, despite the merits of the flexible structure such as its lightweight, low cost, quick reaction, and safer operation, the flexible plate structure is vulnerable to vibrational disturbances [5]. The unwanted vibration leads the plate structural fatigue and durability which affecting the plate stability and performances which subsequently endanger to working environment [6, 7]. Therefore, unwanted vibration must be reduced in order for the plate's performance to be maintained.

Active vibration control (AVC) is a method of suppressing undesired vibration by interfering with the principal disturbance source [8]. To create a successful active vibration control scheme, the system modeling must be realistic enough to replicate the actual dynamic characteristics of the structure [8]. Thus, to implement AVC, determining the accurate and appropriate dynamic model of the flexible plate is crucial. This is a daunting challenge to researchers and engineers attempting to dampen unwanted vibrations so that the flexible structure can be utilized effectively.

Newton-Euler and Euler-Lagrange Formulation are widely used to derive the mathematical model. However, System Identification (SI) is another alternative to determine the dynamic model of the system. SI has been used intensively in flexible structures applications such as flexible plate modeling [9], flexible beam modeling [10], and flexible link arm manipulators [11]. Formerly, conventional parametric estimations have been utilized for modeling the flexible plate structure such as recursive least squares (RLS) [12]. The growth of evolutionary algorithms (EA) in optimization efforts, particularly engineering, has opened up a new research field. The research derived from these efforts is known as intelligent parametric approaches. Researchers model the system by using many different types of evolutionary algorithms such as particle swarm optimization (PSO) [13], artificial bee colony (ABC) [**14hadi2018modeling**], cuckoo search algorithm (CS) [14], chaotic fractal search algorithm (CFS) [15] and prony algorithm [16]. The simplicity of the parametric modeling approach makes most researchers consider it.

Grey Wolf Optimization (GWO) is another evolutionary algorithm that has recently gained popularity in optimization research but has not been applied in estimating flexible plate structure. Due to its exploration and exploitation of the prey structure, which is effective for solving optimization problems [17], it is anticipated that it would be able to perform better for estimating the dynamic modeling of flexible plate structures. These exploration and exploitation processes in the algorithm can prevent the local minima trap suited for large, complex problem search areas like flexible plate structure [18]. Compared to GWO, PSO was widely used in flexible plate structure research because it requires less computational effort. However, it has premature convergence, poor global search ability, and to the ease with which particles fall into the local optimum. This which could result in the failure of the prediction of dynamic modeling parameters obtainment. Thus, GWO demonstrated superior global search capabilities that can sort particles during evolution to find those with the highest fitness value. Likewise, the GWO algorithm has a simple and straightforward procedure and does not require prior knowledge of the problem space [19, 20].

Based on prior research, the optimization effort employing evolutionary algorithms has been demonstrated to be reliable based on the findings in the literature. Despite the fact that various structures in real application are developed at varied angles and are not confined to horizontal and vertical positions, there has been limited research on the plate structure in a tilted orientation. Besides, the advantages demonstrated by GWO over PSO serve as the basis for investigating its capability. Therefore, the study is aimed to model the flexible plate structure with gradient of 30° utilizing SI approach based on GWO algorithm. The attained model will be validated based on input/output mapping, mean squared error (MSE), correlation test and pole-zero stability diagram.

2. Experimental setup

The vibration of a plate can be excited and detected with a suitable experimental setup. In this study, a flexible plate of dimensions of 50 cm × 50 cm × 0.15 cm with a gradient of 30° was investigated. Fig. 1 represents the experimental setup that was constructed for this study.

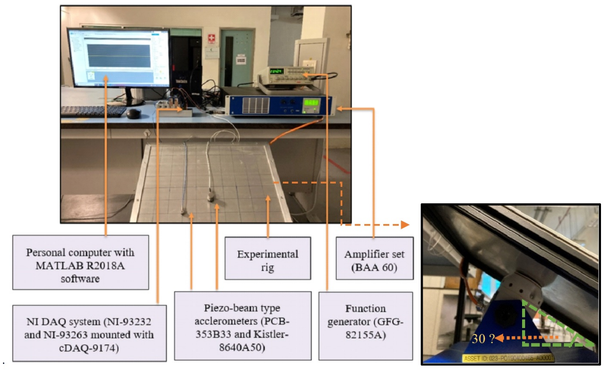


Fig. 1. Experimental rig setup for gradient plate structure with data acquisition system.

The experimental setup was conducted to obtain the input-output vibration data set of gradient flexible plate structure using the National Instruments (NI) data acquisition system. A magnetic shaker was connected to the function generator through a power amplifier which generate a sinusoidal actuation force to excite the experimental gradient plate rig. Two pieces of piezo-beam type accelerometer were attached at observation and detection point respectively to acquire the acceleration signal that represents the vibration of the gradient plate structure. The piezo-beam type accelerometers were connected to NI data acquisition system which was mounted on NI Compact-Data Acquisition (DAQ) which was connected to a personal computer. A personal computer equipped with a 10th Generation Intel® Core^{TM} i3-10105 Processor, 16GB RAM, and MATLAB R2018a software were used to analyze the required signal obtained from the experiment. Fig. 2 depicts the process flow of system integration on the gradient plate structure. The magnetic shaker that was connected to amplifier and function generator would initiate vibration on the flexible plate. Then, the vibration data would be captured by accelerometer and send to computer through DAQ.

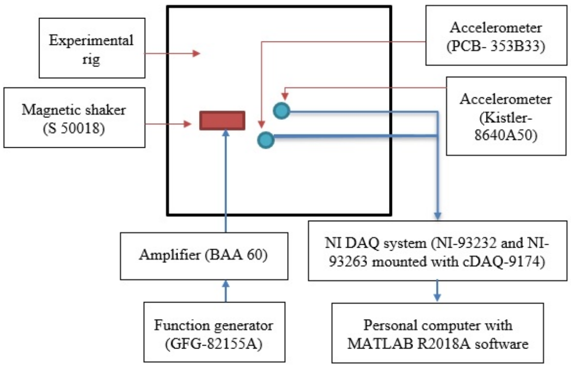


Fig. 2. The layout of experimental setup (blue arrow indicate the process flow of the system integration on gradient flexible plate experimental rig).

3. Grey wolf optimization

GWO is categorized as a stochastic and population-based swarm intelligence algorithm. Grey wolves live in a pack that consists of alpha, beta, delta, and omega. Alpha is the leader that holds the responsibility of decision making. Beta acts as an advisor to the alpha and also acts second in command. Delta plays various roles in scouting, protecting, and caretaking the wolf's pack. Lastly, omega only acts as the followers of the alpha, beta, and delta. In the optimization process, the location of search agents was updated based on the Eqs. (1) and (2) [17]:

$$\vec{D} = |\vec{C}.\overrightarrow{X_p}(t) - \vec{X}(t)| \tag{1}$$

$$\vec{X}(t-1) = \overrightarrow{X_p}(t) - \vec{A}.\vec{D} \tag{2}$$

Where t indicates the current iteration, both $\vec{A}$ and $\vec{C}$ are coefficient vectors, $\overrightarrow{X_p}$ is the vector position of the prey and $\vec{X}$ as the vector position of the wolf. The coefficient vectors $\vec{A}$ and $\vec{C}$ can be expressed by Eqs. (3) and (4) [17]:

$$\vec{D} = 2\vec{a}.\overrightarrow{r_1} - \vec{a} \tag{3}$$

$$\vec{C} = 2.\overrightarrow{r_2} \tag{4}$$

Where the $\vec{r_1}$ and $\vec{r_2}$ are random vectors located in problem space [0,1] while $\vec{a}$ linearly decreased from 2 to 0 over the iteration course. In the GWO algorithm, the position of alpha, beta, and delta are always assumed to be an optimum position which is recorded as the best individual, second-best individual, and third-best individual, respectively. The position of omega was relocated according to the location of alpha, beta, and delta. The Eq. (5) was proposed to update the position of the omega.

$$\vec{D_\alpha} = |\vec{C_1}.\vec{X_\alpha} - \vec{X}|, \vec{D_\delta} = |\vec{C_\varepsilon}.\vec{X_\delta} - \vec{X}| \quad [17] \tag{5}$$

Where $\vec{X_\alpha}$, $\vec{\beta}$, and $\vec{X_\delta}$ were the position vector of alpha, beta, and delta respectively. $\vec{C_1}$, $\vec{C_2}$, and $\vec{C_3}$ were randomly generated vectors and $\vec{X}$ was the position vector of the current individual. The equation in Eq. (5) was calculated as the distances between the position of the current individual and that individual alpha, beta, and delta, respectively. Therefore, the final position vectors of the current individual can be expressed by Eqs. (6) and (7) [17]:

$$\begin{aligned} \vec{X_1} &= \vec{X_\alpha} - \vec{A_1}.(\vec{D_\alpha}), \\ \vec{X_2} &= \vec{X_\beta} - \vec{A_2}.(\vec{D_\beta}), \\ \vec{X_3} &= \vec{X_\delta} - \vec{A_3}.(\vec{D_\delta}) \end{aligned} \tag{6}$$

$$\vec{X}(t+1) = \frac{\vec{X_1} + \vec{X_2} + \vec{X_3}}{3} \tag{7}$$

Where, $\vec{A_1}$, $\vec{A_2}$, and $\vec{A_3}$ were randomly generated vectors and t represents the number of iterations. Fig. 3 depicts the behavior of the GWO algorithm to visualize the algorithm's movement.

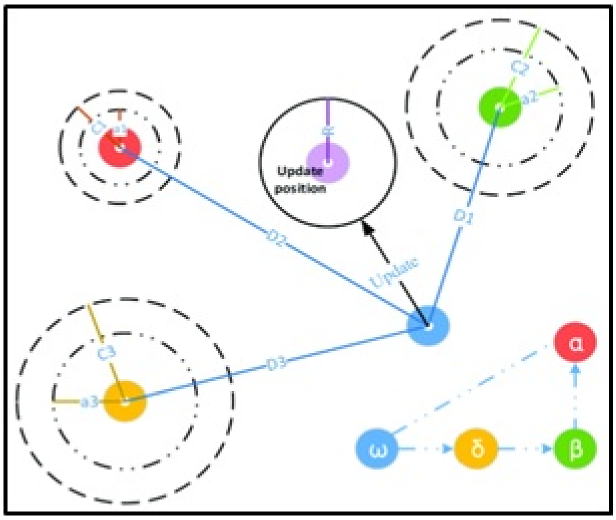


Fig. 3. Schematic diagram of GWO algorithm [21].

4. System identification

SI is a technique developing an optimum model that represents the dynamic system of the structure based on the experimental data acquired. In simple terms, this method develops the approximate model of the real system by using the experimental input-output data from the real system. SI consist of four main steps that is data acquisition, model structure selection, parametric estimation and model validation. Data acquisition which involved the experimental input-output data collection was explained in experimental setup section. The next three steps were explained in the following section.

4.1. Model Structure

A range of model structures is available to assist in modeling a system. The choice of a model structure depends on insight and understanding of the system undergoing identification and understanding of the SI method. Autoregressive Moving Average with Extra Input (ARMAX) provides higher accuracy with less model order as compared to autoregressive with exogenous input (ARX) because the model includes disturbance dynamics. ARMAX models are useful when dominating disturbances appear early in the process, such as at the input. Mathematically the model is given by Eq. (8) [22]:

$$y(t) = -a_1 y(t-1) \ldots - a_n y(t-n) + b_1 u(t-1) \ldots \\ b_n u(t-n) + c_1 \xi(t-1) \ldots c_n \xi(t-n) + \xi(t) \tag{8}$$

Where $y(t)$ is the output signal and $u(t)$ is the input signal, respectively while $\xi(t)$ is the zero-mean white noise in the system. n is the order of the model while $a_1 \ldots a_n$, $b_1 \ldots b_n$, and $c_1 \ldots c_n$ were the parameters of the model. Nevertheless, if the model is acceptable for identifying the system without the noise term, it can be expressed in the ARX model. The ARX model structure is the simplest linear model structure and the most effective estimating approach. ARX model structure was chosen for this study because it is simple and noise can be disregarded in the modeling effort. ARX model structure can be expressed as in Eq. (9) [22]:

$$y(t) = -a_1 y(t-1) \ldots - a_n y(t-n) + b_1 u(t-1) \ldots \\ b_n u(t-n) + \xi(t) \tag{9}$$

4.2. Parametric Estimation

In this work, GWO was used to predict the parametric model. It began by defining the structure of the model, then declared the parameters of interest. The process of obtaining the parameters would be repeated until the optimal values were obtained. The process flow was summarized in the flowchart as shown in Fig. 4.

4.3. Model Validation

The final stage in the SI approach is model validation. Validation of the produced model is crucial to confirm the best model that accurately represents a dynamic system of the gradient flexible plate. For this research, four validation tests were used: one step ahead prediction (OSA), MSE, and correlation tests [23]. Pole-zero diagram stability is an additional test to assess the model's stability before it can be utilized for control development. The flowchart for the validation test and the details of the equation are shown in Fig. 5.

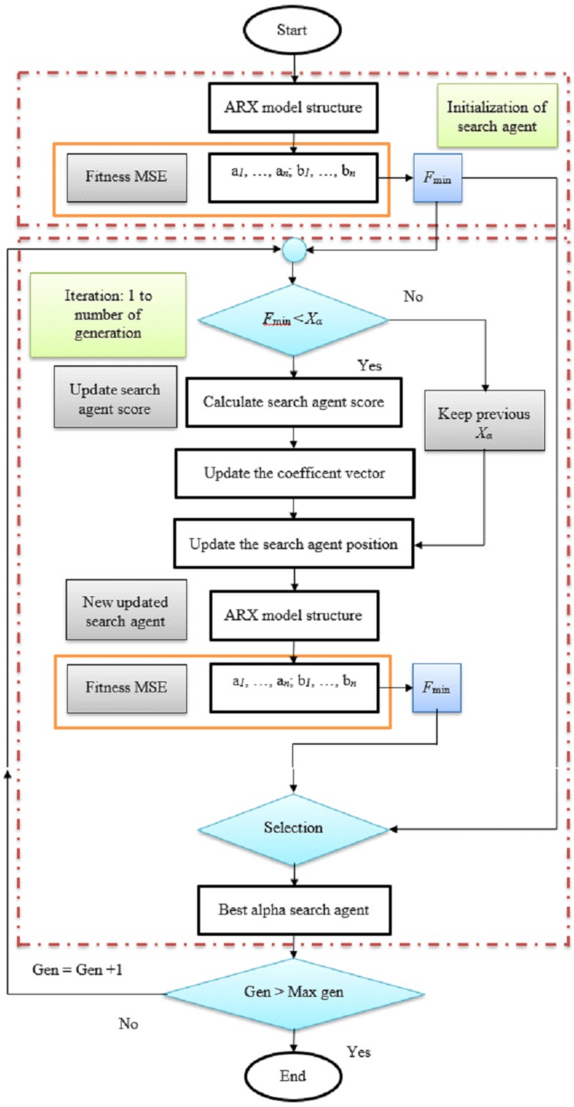


Fig. 4. Flowchart of GWO algorithm for ARX model structure optimization.

5. Result and discussions

In this research, the system model was developed using GWO. The 4000 input-output vibration data obtained from the experiment were divided equally into two parts in order to train and test the quality of developed model. Next, the developed models of the system were validated using MSE, pole-zero diagram and correlation test. The selection of the best model is focused on the evaluation results of the robustness tests which are the lowest MSE, high stability of the pole-zero diagrams and unbiased for correlation test. Validation of the model is one of the important processes to verify the superlative compatible model to personify the structure of the system.

Table 1 summarizes all the parameters of GWO for the

Table 1. Parameters of optimum model for GWO modeling.

Parameter	Value
Number of search agents	50
Number of iterations	500
Lower and upper boundary	-1, 1
Model order	4
MSE for training data	1.3218×10^{-5}
MSE for testing data	8.0496×10^{-6}

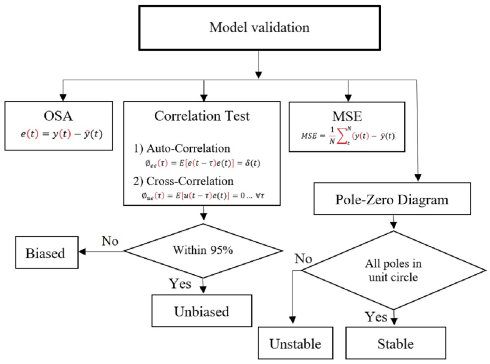


Fig. 5. Flowchart of Model Validation.

developed model together with their MSE values. The optimum model in GWO was determined by varying the model order, the number of search agents, boundary values, and iterations. The numerical results of optimum model order are listed in Table 2. Model order 4 was shown to be the best model order, with MSEs of 1.3218×10^{-5} and 8.0496×10^{-6} for training and testing data, respectively.

Fig. 6 (a)-(b) shows the actual and prediction outputs of the gradient flexible plate system over time, as well as the inaccuracy that occurred between the two. From the results, it showed that there was slight discrepancy between the actual data and predicted data that is 0.0001%. The deviation was very small or close to zero. Thus, the error can be disregarded.

Meanwhile, Fig. 7 shows the estimated outputs in the frequency domain to further investigate the prediction's accuracy. The first three modes of vibration for actual and estimated outputs were found to have the same values. Therefore, it was proven that the developed model was able to imitate the actual output. It can be concluded that the GWO algorithm was able to predict the output accurately.

Figs. 8 and 9 demonstrate the findings of the investigations into stability and correlation, respectively. Stability is essential to ensure that the developed model can be used to design the controller for the system, specifically for systems that implement an AVC to suppress the vibration. Based on the pole-zero diagram, the developed model was proved to be stable with all the poles (x) of the transfer function were inside the unit circle.

Correlation test showed the degrees of the relationship between the two variables. From the results, both auto correlation and cross-correlation tests were found to be within 95% confidence level, confirming the unbiased nature of the developed model. This indicated that the dynamic model obtained herein could represent similar flexible gradient structure with the same setup.

Based on overall model validation, it was demonstrated that the model derived from the GWO model is suitable for representing the gradient flexible plate system for controller development. The transfer function of gradient flexible plate system based on GWO modeling was expressed in Eq. (10);

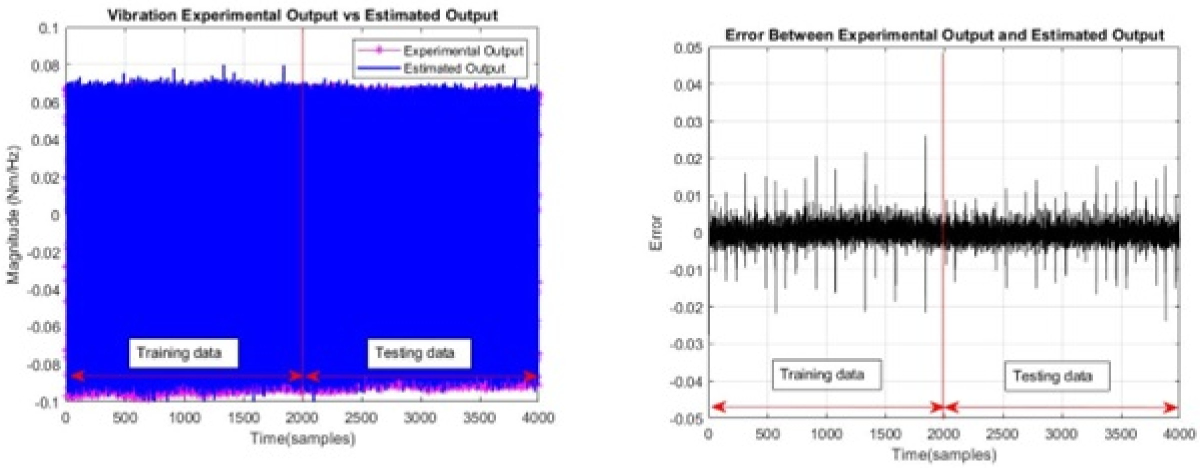
$$H(Z)_{GWO} = \frac{0.3562z^{-1} + 0.1864z^{-2} + 0.4091z^{-3} - 0.3334^{-4}}{1 - 0.7231z^{-1} + 0.383^{-2} - 0.05374z^{-3} + 0.4484z^{-4}} \quad (10)$$

6. Conclusions

The parametric modeling technique using GWO for 30° gradient flexible plate structure using the SI technique has been presented. Results have been validated through OSA, MSE, pole-zero stability, and correlation tests. It was found that the optimum model to represent the dynamic system of gradient flexible plate was achieved by model order 4 with the MSE of 8.0496×10^{-6}. Besides, the correlation test showed the model was unbiased which the graph falls within the 95% confidence level. It is noted that the developed model has performed very well in approximating the system response. The vibration modes of the system have been detected successfully with the modeling techniques considered in this investigation. Therefore, the developed and validated model will be used in subsequent investigations for the development of vibration control strategies of gradient flexible plate structures.

Table 2. Comparison of GWO optimization performance in different number of model order.

Model Order	MSE in training data	MSE in testing data	Stability	Correlation Test
2	1.4206×10^{-5}	1.0696×10^{-5}	stable	biased
4	$\mathbf{1.3218\times10^{-5}}$	$\mathbf{8.0496\times10^{-6}}$	**stable**	**unbiased**
6	1.5621×10^{-5}	6.4077×10^{-6}	stable	unbiased
8	4.7609×10^{-4}	4.2140×10^{-4}	unstable	biased
10	2.0132×10^{-4}	1.6638×10^{-4}	unstable	biased



(a) (b)

Fig. 6. Comparison of Vibration Experimental Output and Estimated Output using GWO for both testing and training data (a) Actual and prediction outputs of the system in time domain (b) Error between actual and estimated output by GWO modeling.

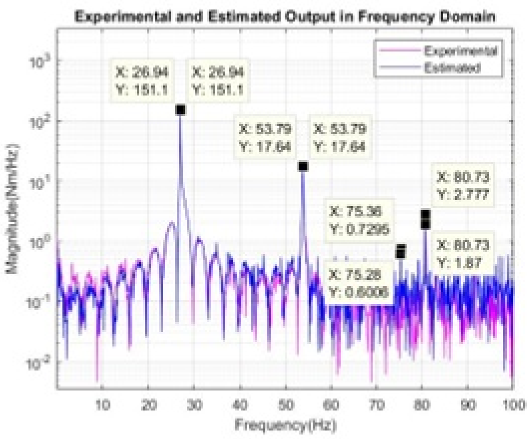


Fig. 7. Comparison of Experimental Output and Estimated Output using GWO in the frequency domain.

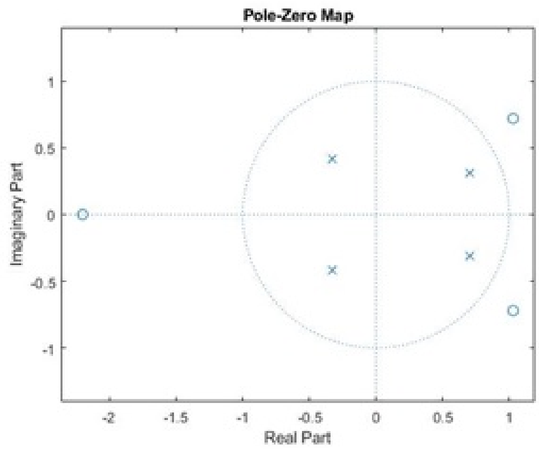


Fig. 8. Pole-zero diagram system of model order 4 by GWO modeling.

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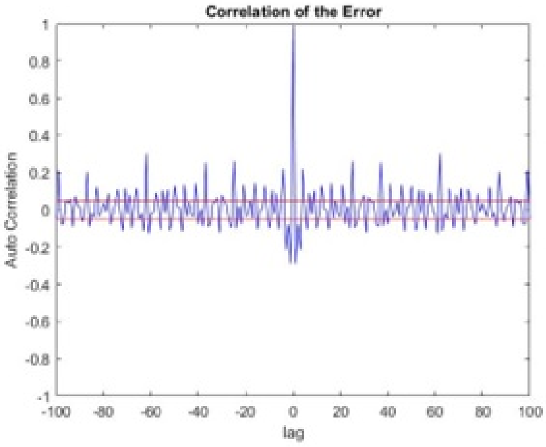
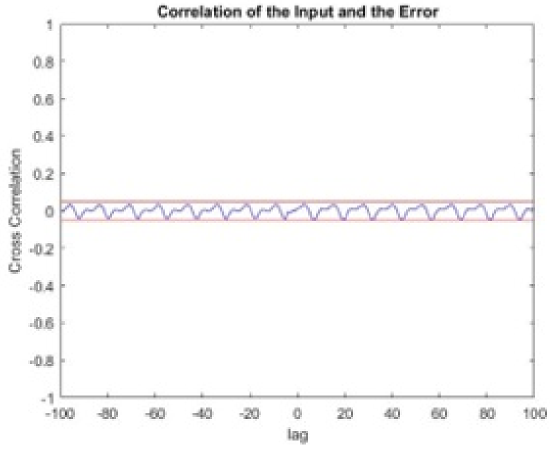


(a)



(b)

Fig. 9. Correlation results between two variables. (a) auto correlation (b) cross-correlation.

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