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A Single Objective Crow Search for Modelling of Horizontal Flexible Plate Structure

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ABSTRACT

The magnificent features of flexible plate structure, including lightweight and high-speed response, resulted in additional market demand, especially in the automotive and manufacturing industries. Nevertheless, the structure may incur structural damage and performance degradation when the system encounters excessive vibration. Therefore, a system identification approach utilising a metaheuristic algorithm via crow search to develop a horizontal flexible plate (HFP) model for vibration control is introduced in this paper. Crow search (CS) is a modern algorithm inspired by a crow's intellectual operation to store additional food and memorise the food storage location. In this study, CS is employed to optimise the objective function, which is the mean squared error for accomplishing a precise predicted model in replicating the dynamic response of the actual structure. Hence, the preliminary action for modelling using this approach is designing and fabricating an HFP rig for experimentally gathering the real input-output vibration data. After that, the mathematical modelling utilising the CS algorithm was implemented using a parametric model structure. Finally, the best-fit model is chosen for the representation of the HFP based on the lowest mean squared error, correlation test within a 95% confidence level and stability in a pole-zero plot. The simulation result reveals that the CS algorithm with a second-order estimated model accomplished a minimum MSE of 1.1168×10^{-5}, an unbiased correlation test and excellent stability for the HFP structure.

Keywords: Active vibration control, crow search, flexible structure, metaheuristic, modelling, swarm intelligence algorithm, system identification

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INTRODUCTION

The effectiveness of a system is always a major concern in an industry, especially when a precise and ample output is needed. Since the 1760s, structures like plates, beams, manipulators and shells have been extensively used to build machinery and other facilities for manufacturing goods. Many human safety and health issues have been recorded in this era as a result of the exploitation of people and animals to perform economic activities for nearly 16 hours per day (Mohajan, 2019). Furthermore, their lives have been put in jeopardy as a result of the massive equipment and rigid structures that they handle.

To date, the government website also has several incidents involving heavy equipment. For instance, on the official website of Malaysia's Department of Occupational Safety and Health (DOSH), two cases resulting in death because of being hit by heavy equipment were registered in February 2019 (Ministry of Human Resources, 2021). In addition, site cleanliness has become a top priority, as large machinery requires a huge amount of lubricant to keep it cool and minimise friction between collided metal pieces, increasing the machine's operating hours. Moreover, according to Mamuda and Mukhtar (2017), fossil fuel-based lubricants influence the climate.

The use of fossil fuel lubricant dates to the first industrial revolution and continues to this day. However, because of its widespread usage in various industries, including transportation, the source of the lubricant is gradually diminishing (Nagendramma & Kaul, 2012). The rise in fatal cases concerning rigid structures and the reduction of non-renewable sources has prompted the growth of facilities and industries employing renewable energy and flexible structure.

Flexible structure, also known as a thin and light structure, has received prominent interest from researchers owing to its numerous advantages (Yatim et al., 2013; Hou, 2018). Nevertheless, the continuous vibration exerted on flexible structures such as plates, manipulators and shells is a crucial issue in the industry. The system efficiency would deteriorate, ultimately leading to total failure, especially when the resonance occurs (Mohammed et al., 2019). This issue has gotten considerable attention in the research sector, particularly in the control and system department.

Most researchers did not want to abandon the structure mentioned above because it has been proven to contribute to economic growth and meets social demands in the future (Agarwal & Agarwal, 2017). As a result, various control techniques for vibration suppression in the system have been identified. However, PID controller is the most prominent industry because of their mobility, less energy usage and require small actuator (Pedro & Tshabalala, 2015). For instance, the implementation of PID controllers has been introduced in autonomous joint dental and flexible systems by Matin et al. (2016) and Tavakolpour et al. (2011).

Although PID controllers have been extensively used in a research area, their effectiveness is often criticised by industry, especially for the non-linear system, due to the uncertainty aspect that the system influences, such as excessive payloads and changes in the operating environment (Visioli, 2012; Nayak & Singh, 2015). Besides that, Rao et al. (2016) stated that the nonlinearities of a system are mainly caused by the failure to obtain an exact model, consequently affecting the controller's accuracy. Therefore, most researchers concentrate on modelling methods before the development of the controller.

Nowadays, scholars have recently focused their study on system identification via swarm intelligence algorithm (SIA) to model a system and solve optimisation problems, including sparse signal reconstruction, sensor characteristics, and seismic response output (Erkoc & Karaboga, 2021; Jiang et al., 2021; Tsipianitis & Tsompanakis, 2021). SIA was motivated by a group of animal and biological interactions allowing them to survive by securing food and hunting prey. Harmony search (HS), genetic algorithm (GA), particle swarm optimisation (PSO), and sheep flock optimisation (SFO) are some examples of SIA employed in the research sector (Gheisarnejad, 2018; Kivi & Majidnezhad, 2021; Khairuddin et al., 2014).

The remarkable benefits of this optimisation approach have also stimulated the interest of researchers in modelling a flexible structure. Hadi et al. (2013) applied PSO in modelling a horizontal flexible plate system. They successfully attenuated the first mode of vibration by 34.37 dB. In addition, Hadi and his coworkers employed an artificial bee colony (ABC) to determine the real characteristic of the flexible plate (Hadi et al., 2014). Furthermore, Eek et al. (2016) and Yatim et al. (2013) have chosen PSO and ABC to develop flexible beam and manipulator structures, respectively. The results indicate a substantial reduction in vibration after the transfer function from the developed model is deployed in the PID controller.

Many topics leveraging various SIA techniques have been published, all of which have yielded outstanding performances, as outlined above. However, one of the disadvantages of an optimisation algorithm is that a lot of parameter setting will lead to time-consuming (Majhi et al., 2020). According to Majhi and his co-investigator, PSO and ABC required 4 tuning parameters, whereas GA needed 6 (Majhi et al., 2020). A new approach based on nature-inspired, namely crow search (CS), has been proposed by Askarzadeh (2016). CS own the same benefit as other global algorithms capable of solving the optimisation problem. Unlike PSO, ABC and GA, which require 4 to 6 tuning parameters, CS, on the other hand, is only dependent on two variables, flight length and awareness probability (Hussien et al., 2020). These two parameters are used to find the optimal solution.

The purpose of this work is to utilise the CS technique to identify a horizontal flexible plate structure. Prior to that, a simulation environment that characterises non-linear characteristics of the horizontal flexible plate structure is developed using a system identification strategy. Initially, input-output vibration datasets are collected experimentally. The dataset acquired is then employed to develop CS-based identification. The responses were extracted in both time and frequency domains. The effectiveness of the developed model also will be validated using correlation tests, pole-zero maps and mean squared error. In addition, this research contributed to modelling a flexible plate structure using a metaheuristic approach via the crow search algorithm.

MATERIALS AND METHODS

Experimental Setup

The input-output vibration datasets of horizontal flexible plate structures are collected using the experimental setup conducted by the previous researcher, as illustrated in Figure 1 (Hadi et al., 2014). The boundary condition of the horizontal flexible plate structure has been modelled with all clamped edges. In this experiment, the flexible structure was mounted in the horizontal plane to let it vibrate vertically. The vibration responses were acquired using the NI data acquisition (DAQ) system through a completed experimental rig with sensors and actuators mounted on a square, flat and thin aluminium plate with dimensions of 0.7 *m* X 0.7 *m* X 0.001 *m*. Table 1 outlines the detailed specifications of the flexible plate employed in this study.

The information flow in DAQ is divided into a few steps. Initially, an actuation force was generated at the excitation point on the test structure by a magnetic shaker positioned 1 *cm* parallel to a circular shape permanent magnet. Next, the excitation on the plate was done by a generation of sine wave force produced using a magnetic shaker linked with a function generator and power amplifier. Then, the acceleration signal is sensed using two pieces of a piezo-beam type accelerometer to represent the vibration of the flexible plate. Next, the accelerometers were installed at two separate locations: detection and observation points. After that, the accelerometers were directly attached to the data acquisition system, which was embedded inside the computer. Finally, utilising specialised software, the collected input-output vibration data were processed, analysed, stored and displayed.

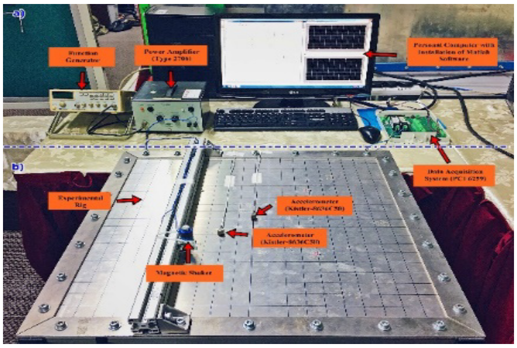


Figure 1. Horizontal flexible plate rig employed in the experiment a) signal conversion using data acquisition system, b) bottom view of the plate (Hadi et al., 2014)

Table 1
The detailed specifications of the flexible plate employed in this study (Hadi et al., 2014)

Parameters	Value
Length, *L*	0.7 m
Width, *w*	0.7 m
Thickness, *t*	0.001 m
Poison ratio, *v*	0.3
Density, ρ	2.17 X 10^3 kgm^{-3}
Modulus of elasticity, *E*	7.11 X 10^{10} Nm^{-2}
Moment of inertia, *I*	5.1924 X 10^{-11} kgm^2

System Identification

Parametric identification was conducted in this research using a linear ARX model structure. In addition, the crow search algorithm (CSA) was utilised as an optimisation technique.

Model Structure. The development of a satisfactory model of the structure can be obtained through a relationship between the input and output of the system. Therefore, it is crucial to obtain an adequate order and parameters for the model that closely fits the input-output data acquired from the experiment to meet this purpose. The Equation 1 of this relationship for the ARX model in zero-order hold can be expressed as:

$$y(t) = \frac{B(z^{-1})}{A(z^{-1})} u(t) \qquad [1]$$

while $A(z^{-1})$ and B(z^{-1}) denoted as

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

$$B(z^{-1}) = b_1 z^{-1} + \cdots + b_n z^{-n}$$

where *y(t)* and *u(t)* depicted the signal input and computed output, respectively with t = 1, 2, 3, …., N. The z^{-1} is indicated as the backshift operator, a_1 ... a_n and b_1 ... b_n are the model parameters, and n is an order of the model. The system parameters that need to be predicted are given by polynomials $A(z^{-1})$ and B(z^{-1}).

The optimisation is based on the mean squared error (MSE) of the difference between real and approximate output, which is described in Equation 2:

$$\mathrm{MSE} = \frac{1}{\mathrm{S}} \sum_{\mathrm{i}=1}^{\mathrm{S}} (|\mathrm{y}(\mathrm{i}) - \hat{\mathrm{y}}(\mathrm{i})|)^2 \qquad [2]$$

y(i) and $\hat{y}(i)$ are measured and estimated outputs, respectively, and S is the sample size. The important aim of system identification is to predict the optimum model parameters that meet the objective function, which in this research is MSE minimisation. Hence, the model development of a horizontal flexible plate structure was obtained by utilising CSA as an optimisation strategy.

Crow Search. The crow search algorithm is a global optimisation approach inspired by crow behaviour, which can be used to find the minimum value of mean squared error. Crows are among the most sophisticated birds, with the largest brain-to-body ratio. They have distinct characteristics, such as self-awareness and the ability to create tools. They employ tools to recognise their hidden food location for a period. Each crow pursues the hidden food supply of another crow and steals it while the owner is away. As a result, every crow takes precautionary measures to secure its food in the best possible location.

Askarzadeh recommended the comprehensive approach following the four basic principles outlined below (Askarzadeh, 2016);

- Crows gather in a cluster, and the population size is defined as flock size, *N*.
- Crows remember the location of their hiding spot and store it as memory, *m*.
- Crows choose and follow one of the other crows in the swarm to steal their food.
- Crows protect their food from being stolen by probability.

Implementation of CS Algorithm to Develop an HFP

The utilisation of the CS algorithm for model development of the horizontal flexible plate structure is discussed as follows (Askarzadeh, 2016).

Stage 1: Problem initialisation and setting parameters. Initially, the optimisation problem and decision variable are defined. The decision variable in this study refers to the number of parameters needed in the ARX structure, where the number is twice the value of the model order. For instance, if the model order is fixed to 2, the problem dimension is 4. The problem dimension consists of parameters that can be addressed as a_1, a_2, b_1 *and* b_2. These values will then be expressed in a transfer function, reflecting the real characteristics of the horizontal flexible plate structure. After that, the adjustable CSA parameters, including flock size (*N*), awareness probability (*AP*), flight length (*fl*), lower (*LB*) and upper boundaries (*UB*) and a maximum number of iterations ($iter_{max}$), are valued. The crows' exploration range in obtaining the possible solution is lower and upper boundaries. For example, if the [LB, UB] ϵ [-4, 4], hence, the crows will explore from the lower bound, *LB* = -4 and *UB* = 4.

Stage 2: Initialisation of crows' position and memory. The location of the crows is specified randomly within the stated range. The values were obtained randomly by using Equation 3:

$$x_{ij} = UB - (UB - LB) \cdot rand_{ij} \qquad [3]$$

where x_{ij} is a number of flocks representing the possible solution within the lower and upper boundary at a random value between 0 and 1, denoted as *rand* in the equation. Each crow embodies a possible solution to the problem. Equation 4 denotes the matrix structure of each crow position in a dimensional search space resulting from the calculated value using Equation 3 (Askarzadeh, 2016).

$$\text{Crows, x} = \begin{bmatrix} x_1^1 & x_2^1 & \dots & x_d^1 \\ x_1^2 & x_2^2 & \dots & x_d^2 \\ \vdots & \vdots & \vdots & \vdots \\ X_1^N & X_2^N & \dots & X_d^N \end{bmatrix} \qquad [4]$$

After that, a memory of the crow is initialised. The initial values of the memory are the same as the current position as they have no prior experiences. Equation 5 shows the matrix form of memory in a dimensional search space (Askarzadeh, 2016).

$$\text{Memory, m} = \begin{bmatrix} m_1^1 & m_2^1 & \dots & m_d^1 \\ m_1^2 & m_2^2 & \dots & m_d^2 \\ \vdots & \vdots & \vdots & \vdots \\ m_1^N & m_2^N & \dots & m_d^N \end{bmatrix} \qquad [5]$$

The numerical examples in this stage can be illustrated as follows:
Number of maximum iterations, $iter_{max} = 10$,
Flock size, $N = 5$,
Awareness probability, $AP = 0.1$,
Flight length, $fl = 2$,
Lower boundary, $LB = -4$,
Upper boundary, UB – 4,
Model order, $mo = 3$,
Number of parameters in ARX structure, $para = 6$ (a_1, a_2, a_3, b_1, b_2, and b_3) – Decision variables

In this situation, each parameter consists of the same lower and upper bounds, which are -4 and 4, respectively. Therefore, if $a_1 = a_2 = a_3 = b_1 = b_2 = b_3 = [-4, 4]$, and let $rand_{11}(0,1) = 0.3124$, $rand_{12}(0,1) = 0.7124$, $rand_{13}(0,1) = 0.1323$, $rand_{14}(0,1) = 0.5512$, $rand_{15}(0,1) = 0.8931$ and $rand_{16}(0,1) = 0.9111$, then each individual representing the initial position are calculated using Equation 3 as:

For $a_1 \in [-4, 4]$ $$x_{11} = 4 - \left(4 - (-4)\right) \cdot 0.3124$$ $$x_{11} = 1.5008 = a_1$$

For $a_2 \in [-4, 4]$ $$x_{12} = 4 - \left(4 - (-4)\right) \cdot 0.7124$$ $$x_{12} = -1.6992 = a_2$$

For $a_3 \in [-4, 4]$ $$x_{13} = 4 - \left(4 - (-4)\right) \cdot 0.1323$$ $$x_{13} = 2.9416 = a_3$$

For $b_1 \in [-4, 4]$ $$x_{14} = 4 - \left(4 - (-4)\right) \cdot 0.5512$$ $$x_{14} = -0.4096 = b_1$$

For $b_2 \in [-4, 4]$ $$x_{15} = 4 - \left(4 - (-4)\right) \cdot 0.8931$$ $$x_{15} = -3.1448 = b_2$$

For $b_3 \in [-4, 4]$ $$x_{16} = 4 - \left(4 - (-4)\right) \cdot 0.9111$$ $$x_{16} = -3.2888 = b_3$$

The calculation above only reflects the first flock and is repeated with subsequent flocks (in this example, the calculation is repeated 5 times with different random numbers). These values can be presented in the matrix structure as denoted in Equation 4. For the numerical example, the values for the first flock are displayed in the first column of the matrix. In addition, since the memory at the initial phase is the same as the position of the crows' value, therefore,

$$Crows, x = Memory, m =$$

$$\begin{bmatrix} 1.508 & 3.1234 & -2.1134 & 0.1108 & 3.9123 & 2.1141 \\ -1.6992 & 0.1451 & -1.1412 & -2.0796 & 1.4231 & -3.9991 \\ 2.9416 & -3.814 & 0.1415 & 3.0081 & -1.982 & -2.132 \\ -0.4096 & 2.9824 & 1.1421 & 2.4071 & -1.932 & 0.3142 \\ -3.1448 & 2.1312 & 1.2411 & -0.2007 & 2.1238 & -1.7282 \\ -3.2888 & -1.9782 & 3.1231 & -1.1091 & 3.8912 & 1.3249 \end{bmatrix}$$

Stage 3: Evaluation of fitness function. The reliability of each crow's location is calculated by integrating the decision variable values into the objective function. In this study, the objective function is to find the minimum values of MSE. As a result, by inserting the values into Equation 2, the fitness function for each flock is calculated and compared. The flock with the lowest values among the 5 flocks is selected as *fmin*. For example, if each fitness function is obtained for a crow shown in Table 2, the current best solution is found at flock 1 with *fmin* = 0.0013 since it has the lowest fitness value.

Table 2
Examples of choosing the initial best solution

	Individual solution (Flock size)				
	1	2	3	4	5
Fitness	0.0013	0.0123	0.0094	0.0841	0.0014

Stage 4: Generation of a new position. The next stage is the generation of the crows' new position. At this stage, by assuming a crow j visits its hiding spot, $m^{j,iter}$ on an iteration, *iter*, and another crow (for instance, crow i) secretly follow the crow j to that spot. There are two possible conditions for this situation which are (Askarzadeh, 2016):

1. Crow j is unaware of the attendance of crow i at its place, $m^{j,iter}$, resulting in crow i entering crow j hiding spot. In this case, the current location of crow i is computed as Equation 6 (Askarzadeh, 2016):

$$x^{i,iter+1} = x^{i,iter} + \mathrm{r_i} \cdot fl^{i,iter} \cdot (m^{j,iter} - x^{i,iter}) \quad [6]$$

where $fl^{\mathrm{i,iter}}$ and r_i represent the crow i flight length at *iter* and random number within 0 and 1 with uniform distribution. The value set for fl is important as it affects the search capability. According to Azkarzadeh, a small and large value of fl results in a local and global search. The effect values of fl on search capability in its current state were thoroughly clarified and demonstrated by Askarzadeh (2016).

2. Crow j is aware that it is being followed by crow i. Hence, it deceives crow i by travelling to a different position in the search space, ensuring its hiding spot remains secure.

Conditions 1 and 2 can be described as Equation 7:

$$x^{i,iter+1} = \begin{cases} x^{i,iter} + r_i \cdot fl^{i,iter} \cdot (m^{j,iter} - x^{i,iter}), r_j \geq AP^{j,iter} \\ a\ random\ position \qquad\qquad otherwise \end{cases} \quad [7]$$

where $AP^{j,iter}$ and r_j depict the awareness probability of crow j at iteration and random number within 0 and 1 with uniform distribution, respectively. The role of *AP* in the CS algorithm is to provide a good balance between diversification and intensification in exploring the search space. The decreases in *AP* value would prompt the CSA to explore a local region where a potentially feasible solution can be discovered. As a result, the intensification will be increased. On the other hand, the increases in *AP* value will reduce the possibility of the current discovery (local region) in finding a good solution, and CSA will attempt to expand the search space on a global level by randomisation (Askarzadeh, 2016).

The following calculation is performed to show the process in stage 4. Assuming the crow j hidden location is shown in Table 3 (Askarzadeh, 2016).

Table 3

Random position of crow j followed by crow i

	Crow j current position at each flock, $m^{j,iter}$				
	1	2	3	4	5
a_1	3.9012	2.9384	2.2417	-2.3113	-2.1234
a_2	0.1293	-2.3181	-1.4156	2.3114	2.1293
a_3	-3.1921	-1.3911	-3.1201	-3.1234	1.2930
b_1	-4.000	1.0292	1.3901	2.3141	-3.1234
b_2	0.7182	-0.9821	1.9241	-3.9182	-1.3914
b_3	-2.1313	-2.4121	1.9020	-1.3481	2.3411

Next, a random number between 0 and 1 was placed in each flock, and a comparison was made with the *AP* value. After that, for any random number greater than the *AP* value, the crow will update its memory using Equation 6. Otherwise, the crow's new position is placed randomly. For example, let $AP = 0.1$, and the random number of all flocks are tabulated as in Table 4 (Askarzadeh, 2016).

Table 4

The random number for the crow i the new position using random distribution

	Random number, r_i				
	1	2	3	4	5
a_1	0.431	0.006	0.912	0.009	0.014
a_2	0.134	0.003	0.120	0.014	0.009
a_3	0.001	0.914	0.100	0.566	0.001
b_1	0.032	0.009	0.039	0.003	0.014
b_2	0.340	0.521	0.020	0.102	0.011
b_3	0.002	0.011	0.410	0.001	0.912

The current memory of crow *j,* which satisfies condition 1, will be updated by substituting the required values in Equation 6. Therefore, the new position of crow *j* at $x_{36}^2 = -3.2680$. While the position of crow x_{16}^2, which satisfies condition 2, is placed randomly using Equation 3. The calculation is performed for each flock.

For b_3 at flock 3 $\quad x_{36}^2 = -3.2888 + (0.002)(2)\big(1.9020 - (-3.2888)\big)$

(r > AP) $\quad x_{36}^2 = -3.2680$

For b_3 at flock 1 $\quad x_{16}^2 = 4 - \big(4 - (-4)\big) \cdot 0.3131$

(r < AP) $\quad x_{16}^2 = 1.4952$

Stage 5: Feasibility check of the new position. The generation of the new position is checked. If the solution is feasible, replace the crow position with a new one. Otherwise, the position is not updated.

Stage 6: Evaluation of fitness function at new positions. The new position of each crow is evaluated by measuring its fitness function using Equation 2. For example, the new fitness function is presented in Table 5. Hence the best new solution is found at flock 4 with *fmin* = 0.03 X 10^{-5} since it has the lowest fitness value.

Table 5

Examples of choosing the best new solution

	Individual solution (Flock size)				
	1	2	3	4	5
New Fitness (× 10^{-5})	1.82	3.21	0.91	0.03	4.12

Stage 7: Update memory. The crows update their memory as Equation 7 (Askarzadeh, 2016):

$$m^{i,iter+1} = \begin{cases} x^{i,iter}\ ,\ f\left(x^{i,iter+1}\right)\ is\ better\ than\ f\left(m^{i,iter}\right) \\ m^{i,iter}\ ,\ otherwise \end{cases} \quad [7]$$

where *f(.)* indicates the measured objective function value. Hence, $f\left(x^{i,iter+1}\right)$ denotes the objective function value for the new position at the current iteration, while represents the objective function of the crow's previous memory location. This stage involves comparing the fitness function of a crow's current and memorised positions. If the fitness function of the new position is better than the memorised position's, the crow will replace its memory with a new position.

Now, by comparing the fitness value in Tables 2 and 5, the memory of the crow will update according to the rules (Table 6).

Table 6

Comparison of fitness value between the initial and new position

	Individual solution (Flock size)				
	1	2	3	4	5
Fitness	0.0013	0.0123	0.0094	0.0841	0.0014
New Fitness (× 10^{-5})	1.82	3.21	0.91	0.03	4.12

Since all new positions achieved better fitness value than memorised positions, all crows will update their memory with a new position as calculated at stage 4 (Table 7).

Table 7

Updated position of a crow after evaluation

	Updated position of crow *i* at each flock, $x^{i,iter+1}$				
	1	2	3	4	5
a_1	3.9121	3.0121	3.9123	-2.8172	-3.9121
a_2	0.2033	-4.000	-2.8192	3.9817	1.0928
a_3	-1.234	-2.421	-4.000	-3.7167	3.0912
b_1	-3.8122	1.4214	2.6172	2.9182	-1.9821
b_2	1.2314	-2.9125	2.8123	-1.8264	-2.0918
b_3	1.4952	-3.9128	-3.2913	2.0918	3.6710

Stage 8: Check termination criterion. The stages from 4 until 7 are performed until $iter_{max}$ is achieved. The optimisation task is completed after the termination condition is satisfied. Finally, the global minimum fitness value is obtained, which refers to the optimal parameter for the ARX structure.

From a numerical example, let $iter_{max}$ = 10 and model order = 3. After the generation of new positions of all crows is done 10 times, the optimisation task will stop from finding the solution. Hence, the final result for 10 iterations can be seen in Table 8. After completing the 10th generation, best fitness = 0.08×10^{-5}. The value of the best solution converged at the 7th iteration as the value remained unchanged until the last iteration.

Table 8

Generation of new position until ten iterations

Generation	1	2	3	4	5
a_1	0.312	0.141	0.981	1.921	0.012
a_2	0.051	0.248	1.891	0.012	1.002
a_3	1.001	1.002	0.910	0.021	0.041
b_1	1.321	0.023	1.902	0.231	0.007
b_2	0.012	1.023	0.101	0.009	0.001
b_3	1.001	0.031	1.451	1.021	1.023
Fitness ($\times 10^{-5}$)	1.901	1.589	1.209	0.101	0.102

The best solution is kept and substituted in the transfer function Equation 8 to represent the horizontal flexible plate structure.

$$\frac{y(t)}{u(t)} = \frac{a_1 z^{-1} + a_2 z^{-2} + a_3 z^{-3}}{1 + b_1 z^{-1} + b_2 z^{-2} + b_3 z^{-3}} \qquad [8]$$

The pseudocode and flowchart of the optimisation task using CS are illustrated in Figures 2 and 3 (Askarzadeh, 2016).

Crow Search Algorithm
Initialize a random number of crow position in flock, *N* in the dimensional search space
Initialize the maximum number of iterations, $iter_{max}$
Evaluate the crows' position
Initialize each crow memory
while $iter < iter_{max}$
for *i*: *N* (all *N* crows (crow *i)* of the flock
$Crow_i$ randomly follow one of the other crows (for instance *j*)
Define an awareness probability, *AP*
if $r_j \geq AP^{j,iter}$
$x^{i,iter+1} = x^{i,iter} + r_i \cdot fl^{i,iter} \cdot (m^{j,iter} - x^{i,iter})$
else
$x^{i,iter+1} = a\ random\ position$
end if
end for
Check the quality of crow new positions
Evaluate the new position of the crows using Equation [2]
Update the crow memory
end while

Figure 2. Pseudo code for the CSA optimisation (Askarzadeh, 2016)

RESULTS AND DISCUSSIONS

In this study, the dynamic model of a horizontal flexible plate was developed using a system identification technique via swam intelligent algorithm known as crow search (CS) by utilising ARX structure. The parameters of the developed model were determined using MATLAB software. These parameters were given in the form of a transfer function, representing the real characteristics of the horizontal flexible plate structure. Initially,

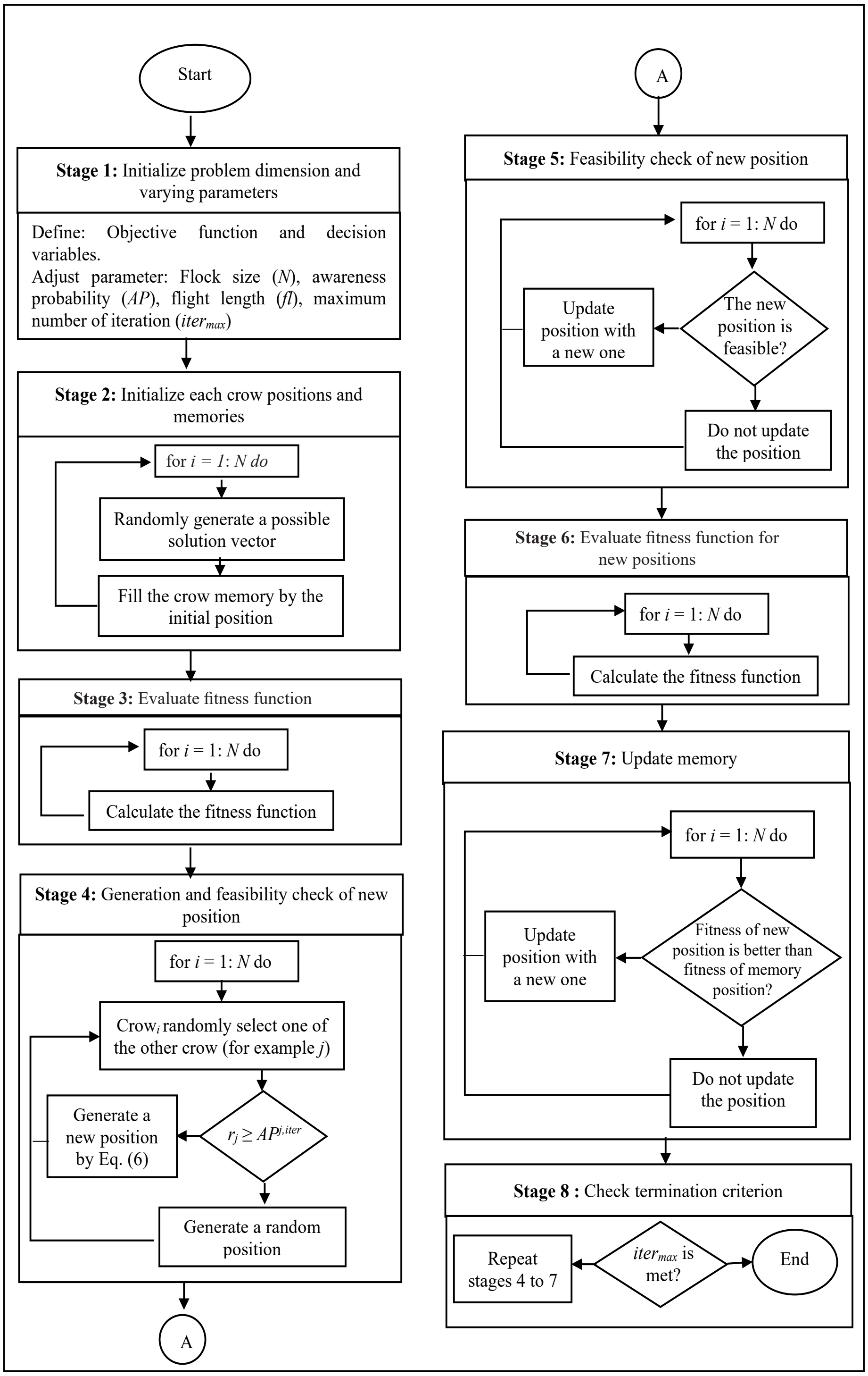


Figure 3. Flowchart of CSA (Askarzadeh, 2016)

5000 input-output vibration datasets extracted through experiments are split into two sections. The first 2500 data points were employed for training, and the remaining 2500 were employed for testing. The effectiveness of the developed model was evaluated using three robustness approaches: pole-zero maps, correlation analysis, and mean squared error (MSE). A high-quality model was selected based on the lowest MSE, unbiased in correlation tests and stable result in a pole-zero map. Furthermore, a heuristic approach was used to obtain the best model order for the proposed structure because there is no prior information regarding the right model order for the model above. This approach was executed by tuning one parameter per variable while leaving the other parameter unchanged.

Six parameters were tuned heuristically in the CS tuning process, including several iterations, model order, population size, lower and upper boundaries, awareness probability and flight length. Although most research papers claimed that CS consists of only two parameters, in this study, all parameters were tuned to validate the statements. Based on the literature review, some implementations use different values for population size, awareness probability and flight length (Souza et al., 2018; Islam et al., 2020). On the other hand, Adhi et al. (2018) and Majhi et al. (2020) tuned the lower and upper boundaries for their applications. Due to the inconsistencies of the parameter setting in the previous works, all parameters were considered and observed in this analysis.

The tuning phase began by varying the population size while the remaining parameters stayed unchanged. In this research, the population size was tuned from 5 to 45 because previous analyses discovered these values offered superior results for most optimisation problems (Islam et al., 2020; Askarzadeh, 2016). Once the best population size value was determined, the value was set, and the next parameter was adjusted. Next, the awareness probability was set from 0.05 until 0.45 with an increment of 0.05. Following that, the range of flight lengths and boundary limits were adjusted from 0.5 to 2.5 and 1 to 10, respectively. Next, the number of iterations was adjusted based on the previous researchers' recommendations, which ranged from 100 to 500 with an increment of 100 (Souza et al., 2018; Majhi et al., 2020). The iteration was terminated at 500 because the outcomes were consistent, which helped reduce the computational time. Finally, the model order was tuned from 1 to 10.

The second order was the best model order, achieved with the parameters outlined (Table 9). The second order is considered the optimal and most preferable in control design. The controller analysis can be simplified by using fewer parameters in the transfer function (Okiy et al., 2015; Aly, 2013). In addition, the graph of convergences for the CS algorithm against iteration was plotted in Figure 4. The graph depicts the accelerated convergence rate for CS to explore the search space to find the best solution. According to previous studies, the CS algorithm converged faster than other algorithms like GA and ABC (Hadi et al., 2012). Furthermore, Figures 5 and 6 indicate the measured and predicted outputs of the horizontal flexible plate structure in the time and frequency domains. The developed CS model managed to imitate the real structure because they overlapped (Figures 5 and 6).

In order to assure the reliability of the developed model, three validations were conducted: pole-zero diagram, correlation analysis, and mean squared error. The MSE for the developed model using CS are 1.6205×10^{-5} and 1.1168×10^{-5} for training and testing results, respectively. This finding was compared to previous studies that used GA to model a flexible plate using the same experimental data set (Hadi et al., 2012). The developed model using CS outperformed the GA model in terms of MSE and the number of orders in the transfer function. Additionally, the error between the real and CS outputs is illustrated in Figure 7. Figures 8 and 9 display the correlation analysis and pole-zero map results. The correlation analysis is comprised of two tests, cross and autocorrelations. Only cross-correlation was observed to be unbiased from this correlation analysis since the response was within the 95% correlation test. The pole-zero diagram reveals that all the poles are located in the unit circle, resulting in a stable outcome. Finally, Equation 9 describes the transfer function representing the best horizontal flexible plate structure model.

$$\frac{y(t)}{u(t)} = \frac{0.384z^{-1} - 0.002184z^{-2}}{1 - 1.414z^{-1} + 0.9931z^{-2}} \quad [9]$$

Table 9

The best value of parameters achieved in developing the CS model

Parameters	Values
Number of flocks	15
Awareness probability	0.1
Flight length	2
Lower and upper boundary	[-10,10]
Model order	2
Iteration	200

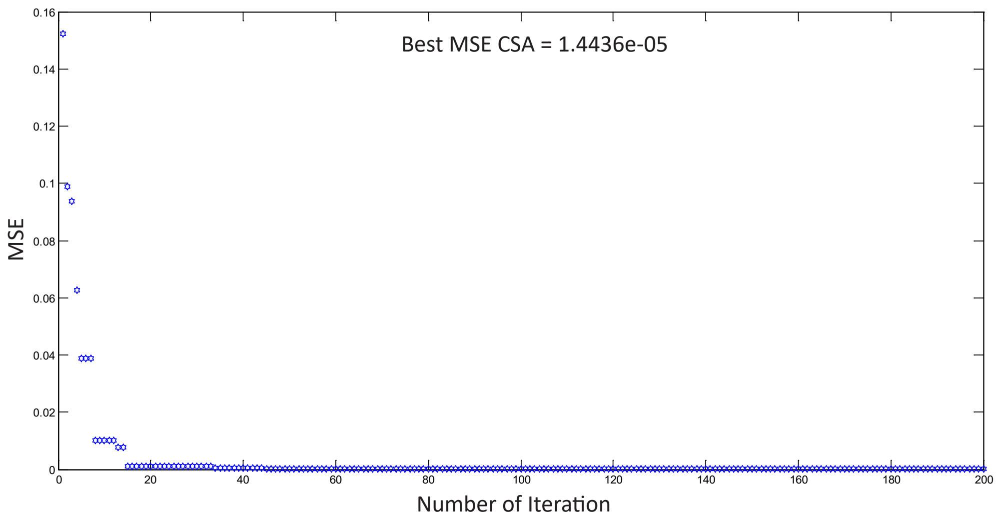
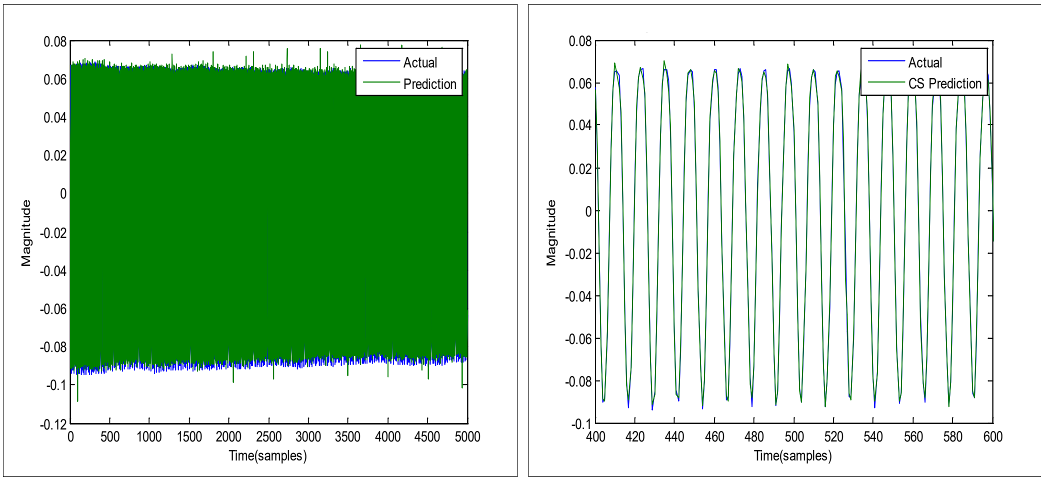


Figure 4. Convergence graph of the estimated model using CSA



(a) (b)

Figure 5. Experimental and CS model in the time domain for flexible plate structure (a) for 5000 data; (b) an extended view of the data from 400 to 600

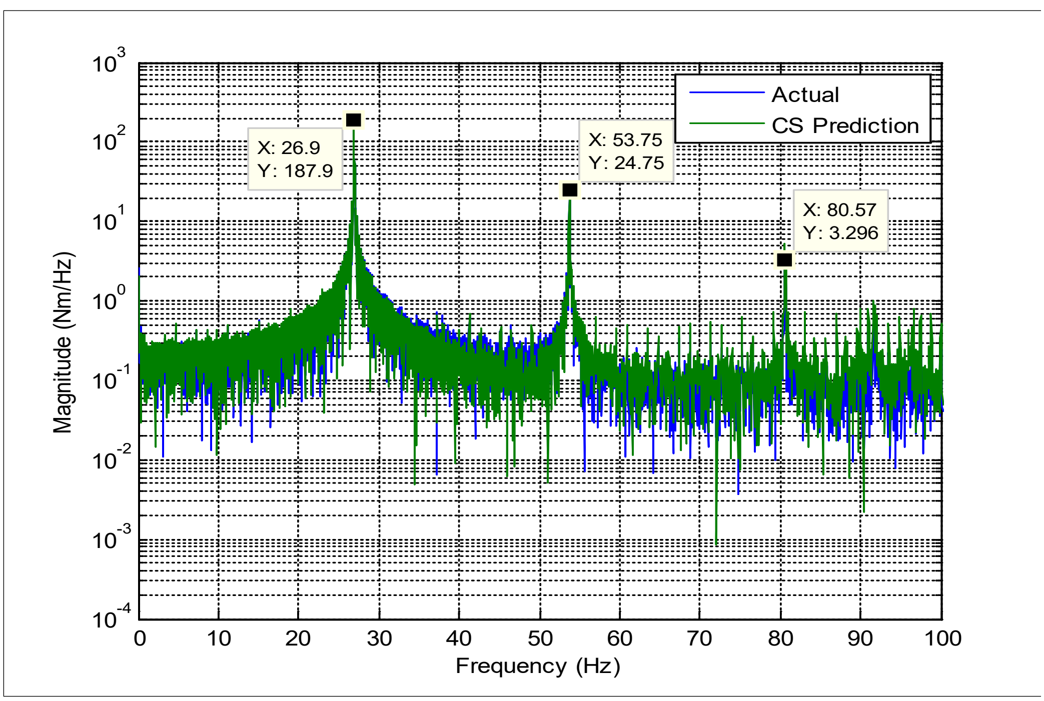


Figure 6. Experimental and CS model in the frequency domain for flexible plate structure

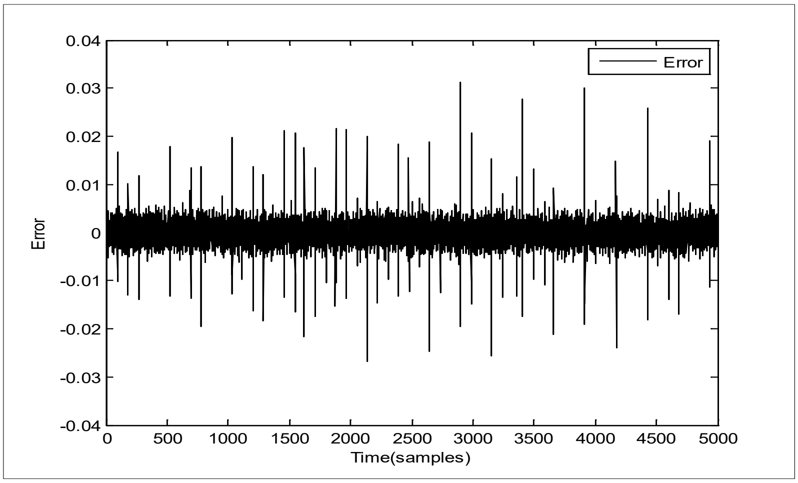


Figure 7. Calculated MSE between the experimental and CS model for flexible plate structure

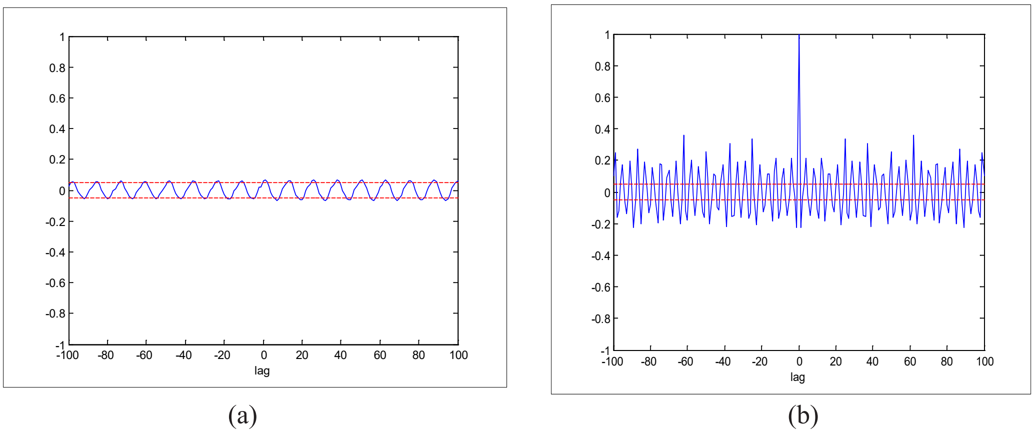


Figure 8. Correlation of the error for CS algorithm in (a) cross-correlation; (b) auto-correlation

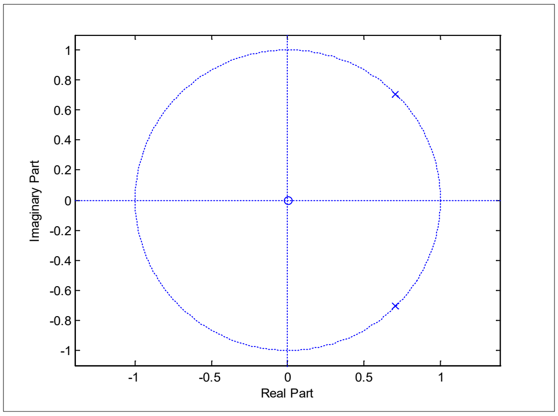


Figure 9. Pole-zero diagram

CONCLUSION

This paper presented an optimisation approach using a swarm intelligence algorithm via crow search for model development of horizontal flexible plate structure. The CS flow is described in detail to obtain an accurate system model. The developed model was validated using correlation analysis, mean squared error and pole-zero map. It is worth noting that the developed model utilising CS has performed well in predicting the system characteristics because it fulfilled all the validation requirements. Furthermore, the developed model achieved the lowest MSE, unbiased in the correlation test and stable in the pole-zero map. In addition, a comparison with previous studies shows that the CS algorithm is superior in modelling a horizontal flexible plate structure. Hence, the aim of this study to utilise the CS technique for the identification of a horizontal flexible plate structure is accomplished. The results achieved can be used to develop a robust and effective controller.

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