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Research Paper

Model Updating for Large-Scale Railway Bridge Using Grey Wolf Algorithm and Genetic Alghorithms

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ABSTRACT

This paper proposes a novel hybrid algorithm to deal with an inverse problem of a large-scale truss bridge. Grey Wolf Optimization (GWO) Algorithm is a well-known and widely applied metaheuristic algorithm. Nevertheless, GWO has two major drawbacks. First, this algorithm depends crucially on the positions of the leading Wolf. If the position of the leaderis far from the best solution, the obtained results are poor. On the other hand, GWO does not own capacities to improve the quality of new generations if elements are trapped into local minima. To remedy the shortcomings of GWO, we propose a hybrid algorithm combining GWO with Genetic Algorithm (GA), termed HGWO-GA. This proposed method contains two key features (1) based on crossover and mutation capacities, GA is first utilized to generate the high-quality elements (2) after that, the optimization capacity of GWO is employed to seek the optimal solutions. To assess the effectiveness of the proposed approach, a large-scale truss bridge is employed for model updating. The obtained results show that HGWO-GA not only provides a good agreement between numerical and experimental results but also outperforms traditional GWO in terms of accuracy.

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1 Introduction

For many years, Structural Health Monitoring (SHM) of large-scale civil infrastructures, such as bridges, dams, skyscrapers, etc, has been under substantial deliberation among the engineering community [1-4]. The goal of SHM is to prevent any catastrophic damages which may hinder the serviceability and lifecycle of the structures. Within a SHM system,

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structural identification plays a vital role in ensuring its accuracy and effectiveness. It requires the integration of Finite Element (FE) model, data processing, model updating, and decision-making [5]. Experimental measurement is conducted to identify the physical characteristics of the structure; any changes in these properties will result in changes within the experimental measurement data. Hence in order to accurately identify the physical characteristics of the structure, it is vital to conduct experimental measurements and correlate the data from the experimental and the numerical model. The process of calibrating FE model to represent as closely as possible the dynamic characteristic of the real-life structure is called model updating. In model updating, mathematical techniques are applied extensively to minimize the difference between the experimental and the numerical model. Brownjohn et al. [6] proposed a novel method combining dynamic testing and modal analysis for model updating of a refurbished highway bridge. The result shows that the accuracy level for modal updating of the bridge model has increased to 50% more than before. Feng et al. [7] proposed a novel model updating method based on in-situ dynamic displacements instead of modal parameters to update a railway bridge. The results have shown much better accuracy in updating the bridge model when compared with the traditional method using modal parameters. Innovative methods using strain energy and modal flexibility are also introduced by Jaishi et al. in [8] and [9] to update and detect structural damage of beam-like structures with a high level of efficiency. Ren et al. [10] proposed an improved method using the response surface model for FE model updating of a full-size bridge. The method not only has a high level of accuracy but also requires less computational cost than the traditional sensitivity-based method.

During the FE model updating process, especially for complex structures, one of the main issues researchers have to face is the tendency of the updating methods to get trapped in local minima instead of the global minima, which may result in a high level of errors of the updating result. To alleviate this problem, many researchers have turned to use Optimization Algorithm (OA) as an assisting tool to improve the effectiveness of FE model updating. With the ability to solve complex problems at a fast convergent rate, OA has attracted the attention of many researchers [11]. Hoa Tran et al. [12] presented the application of Particle Swarm Optimization (PSO) and GA for model updating and damage detection of a real-life truss bridge. The proposed method helps to reduce the difference between the experimental and numerical models significantly. Deng et al. [13] introduced GA with the response surface method to update a beam structure, with GA being implemented to find the best solution for the objective function. Jung et al. [14] introduced a modified GA to update a small-scale bridge with much higher accuracy in comparison with the traditional GA.

In this paper, we introduce a novel model-updating technique using a combination of the GWO and GA to update the model of a large-scale railway bridge. The proposed method can overcome drawbacks of tradional GWO based on crossover and mutation operators of GA and wide space search capacities of GWO.

The paper is organized as follows: after the introduction, section 2 presents the methodology of this work including GWO, GA, and a combination of GWO and GA. Model updating for Nam O bridge is introduced in section 3. Finally, some key conclusions are given.

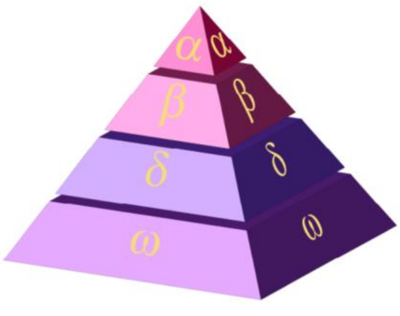


Fig. 1 – Hierarchy of grey wolf (dominance decreases from top down)

2 Methodology

2.1 Grey Wolf optimization algorithm

The GWO was first introduced by Mirjalili et al. [15] in 2014. Since then, GWO has quickly gained attention from the research community as a powerful optimization tool. GWO is a metaheuristic algorithm inspired by the hunting behavior of grey wolf and their hierarchy system within a pack. Each wolf pack usually consists of 5 to 12 individuals, with a strict hierarchical system (see Fig. 1**Erreur ! Source du renvoi introuvable.**) applied to the whole pack to ensure the efficient hunting and survivability of the pack. The mathematical model of GWO mimics this hierarchy pyramid of a grey wolf pack, as shown in Fig. 1. The best possible solution selected is denoted as alpha (α), which represents the leader of the wolf pack in real life. The second and third best solutions are assigned as beta (β) and delta (δ), respectively. The rest of the candidate solutions are assigned as omega (ω). In GWO, the hunting process is led by α, β, and δ, ω will strictly follow the three solutions. The hunting process of GWO consists of three main steps: Encircling prey, Hunting, and attacking. The details of each step are explained in section 2.3 of this paper.

2.2 Genetic Algorithm

Since its first introduction in 1973, GA has become one of the most widely used metaheuristic optimizations in solving various complex engineering problems. The optimization is inspired by Charles Darwin's theory of biological evolution [16], which indicates the survivability of species through a process of genetic selection, crossover, and mutation. The selection process determines the selection of input individuals randomly using different selection methods such as Boltzmann selection, Roulette Wheel selection, etc. The selection also determines the convergence rate of GA in solving optimization problems. In this research, the Roulette Wheel selection is chosen since it can prevent premature convergence from happening. Crossover and Mutation operators are tasked to generate and diversify the next offspring by a genetic combination of the "parents" individuals and genetic mutation of the breeding. These three operators are repeated until reaching the maximum iteration numbers to obtain the best possible solution, thus, they enable this algorithm to be capable of searching for the global optimum required.

2.3 Hybrid Grey Wolf algorithm and Genetic Algorithm

In this paper, a hybrid algorithm combining GWO and GA is proposed with the aim of fusing the strengths of both composing algorithms. In GWO, although the number of omega individuals is much higher than that of the leader alpha, beta, and delta wolves, they depend entirely on the commands of those three groups. This is one of the main shortcomings of GWO where the omegas are only tasked to store the best values instead of joining the search process. To remedy this issue, the hybrid HGWO-GA applies the crossover and mutation process of GA to the omega individuals to re-select the leader among the omegas to join the search. This helps to avoid the missing of global minima as well as increasing the convergent rate of the search. The main steps of HGWO-GA are detailed as follows:

Step 1: Encircling prey

In real life, the first step of a wolf pack's hunting process is to encircle the prey once they are identified. The encircling prey is mathematical modeled as Equation (1) and (2) below to calculate the distance between the wolf and the prey:

$$\vec{D} = \left|\vec{W} \cdot \overrightarrow{X_p}(it) - \vec{X}(t)\right| \tag{1}$$

$$\vec{X}(it+1) = \overrightarrow{X_p}(it) - \vec{A} \cdot \vec{D} \tag{2}$$

Where it is the current iteration, $\overrightarrow{X_p}$indicates the position of the prey, $\vec{X}$ indicates the position of the wolf,$\vec{A}$and $\vec{W}$ are the distance coefficient vectors, which are calculated as follows:

$$\vec{A} = 2\vec{a} \cdot \overrightarrow{r_1} - \vec{a} \tag{3}$$

$$\vec{W} = 2 \cdot \overrightarrow{r_2} \tag{4}$$

Where $\overrightarrow{r_1}, \overrightarrow{r_2}$ are random vectors in $[0, 1]$, $\vec{a}$ is a vector that decreases linearly from 2 to 0.

Fig. 2illustrates the possible distances in 2D and 3D between the wolf and the prey as calculated in Equations (1) and (2). (X, Y) is the coordinates of the wolf's position, and $(X *, Y *)$is the coordinates of the prey's position accordingly. The wolf can update its position as the prey moves. The best possible position for the wolf can be adjusted by modifying the coefficient vectors. The random vectors in (3)and (4) allow the wolf to update its positions arbitrarily between all the points in both the 2D and 3D spaces. This idea can also be applied to a larger search space where the wolves can update their positions in hyper-spheres shapes.

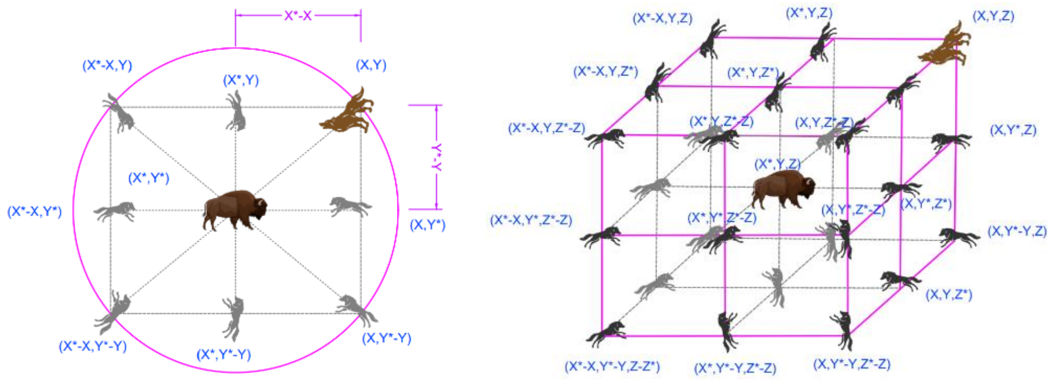


Fig. 2 – 2D and 3D solutions

Step 2: Hunting

In the original GWO, once the prey is located and encircled, the leader alpha wolf will lead the pack for hunting. The beta and delta wolves can also join the hunt. However, the position of the prey is unknown in their search space, In the mathematical model of the grey wolf's hunting process, the alpha individual is assumed to be the best candidate solution, and beta and delta individuals are the second and the third best candidates, respectively. These three candidate solutions will be stored and used to update the position for the omegas to follow the search.

The original GWO depends entirely on the alpha, beta, and delta individuals to update the positions for the rest of the solution without taking advantage of the search ability of the remaining omegas. Therefore, this paper proposed an improved method using genetic algorithm to further develop the set of leaders within the omegas to guide the hunt, so-called HGWO-GA. A percentage of the population px is selected to increase the chance of finding the position of the best possible solution. Crossover and mutation processes are applied to the selected percentage of population px to generate the best candidate solution denoted as $\overrightarrow{D_\zeta}$ and $\overrightarrow{D_\eta}$,respectively. In this case, instead of updating the positions entirely from alpha, beta, and delta as shown in Equation (6), two additional means to update the position based on crossover ($\overrightarrow{X_\zeta}$) and mutation ($\overrightarrow{X_\eta}$) are added as $\overrightarrow{X_4}$ and $\overrightarrow{X_5}$ in Equation (7). The mathematical equations of the hunting step are shown below:

$$\overrightarrow{D_\alpha} = \left|\overrightarrow{W_1}\cdot\overrightarrow{X_\alpha} - \vec{X}\right|;\ \overrightarrow{D_\beta} = \left|\overrightarrow{W_2}\cdot\overrightarrow{X_\beta} - \vec{X}\right|; \overrightarrow{D_\delta} = \left|\overrightarrow{W_3}\cdot\overrightarrow{X_\delta} - \vec{X}\right|;$$
$$\overrightarrow{D_\zeta} = \left|\overrightarrow{W_4}\cdot\overrightarrow{X_C} - \vec{X}\right|; \overrightarrow{D_\eta} = \left|\overrightarrow{W_5}\cdot\overrightarrow{X_M} - \vec{X}\right| \tag{5}$$

$$\overrightarrow{X_1} = \overrightarrow{X_\alpha} - \overrightarrow{A_1}\cdot\left(\overrightarrow{D_\alpha}\right), \overrightarrow{X_2} = \overrightarrow{X_\beta} - \overrightarrow{A_2}\cdot\left(\overrightarrow{D_\beta}\right), \overrightarrow{X_3} = \overrightarrow{X_\delta} - \overrightarrow{A_3}\cdot\left(\overrightarrow{D_\delta}\right)$$
$$\overrightarrow{X_4} = \overrightarrow{X_\zeta} - \overrightarrow{A_4}\cdot\left(\overrightarrow{D_\zeta}\right), \overrightarrow{X_\eta} = \overrightarrow{X_\eta} - \overrightarrow{A_5}\cdot\left(\overrightarrow{D_\eta}\right) \tag{6}$$

$$\vec{X}(t+1) = \frac{\overrightarrow{X_1} + \overrightarrow{X_2} + \overrightarrow{X_3} + \overrightarrow{X_4} + \overrightarrow{X_5}}{5} \tag{7}$$

Fig. 3 illustrates the position updating process for alpha, belta, delta, zeta and eta in a 2D search space, respectively. Alpha, belta, delta, zeta, and eta wolves can locate and encircle the prey to guide the rest of the omega wolves to update their position around the prey.

Step 3: Attacking prey.

The moment the prey stops moving, the wolves shall end the hunt by attacking the prey. This process is mathematically modelled by decreasing the value of the vector linearly $\vec{a}$as mentioned in the first step. It is noted that the variation of $\vec{A}$can also lead to a decrease in the value of$\vec{a}$. When $\vec{A}$ has a random value from $[-1, 1]$, the next position of the search agent can be one of the points between the current position and the position of the prey. When $A < 1$, the wolf will attack its prey, and when $A > 1$, the hunt will continue. Fig. 3presents the conditions for the wolf to attack its prey.

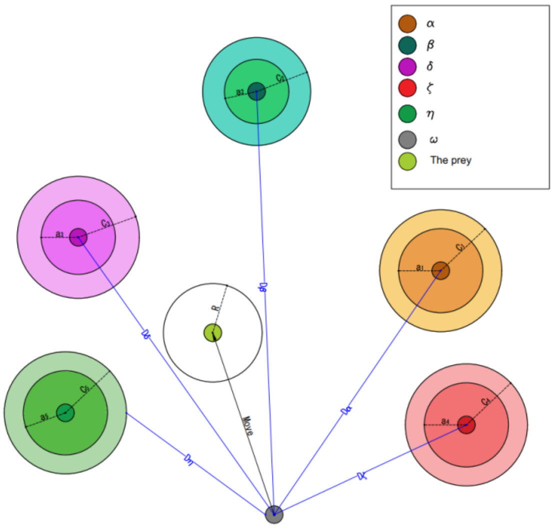


Fig. 3 – Position updating in HGWO-GA

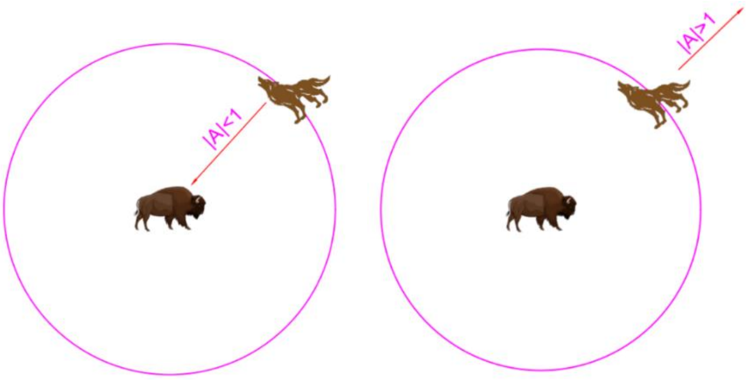


Fig. 3 – Attacking prey versus searching for prey

Search for prey (exploration).

In the original GWO, the grey wolves entirely depend on the position of the alpha, beta and delta while ignoring the search ability of the omegas. Therefore, HGWO-GA has included zeta and eta selected from the omegas to increase the search agent to make use of the crossover and mutation process of the GA. To extend the search for random values of the algorithm, the parameters A and C are defined as shown in Equation (3) and (4) above. When $A < 1$, the wolf will attack its prey, and when $A > 1$, the wolf will look for another prey instead. C is a random parameter which weights the importance of the position of alpha, beta, delta, zeta, and eta in hunting the prey. $C < 1$ means the position is less important than the others while $C > 1$ is vice versa. The randomness of the algorithm is also expressed through the crossover and mutation process of a specific percentage of population px . This helps HGWO-GA get the most stochastic states during the search for optimal global solution and avoid getting trapped in local minima.

In summary, the search process begins with the generation of a random population of grey wolves (candidate solutions) in the HGWO-GA algorithm. During the iteration, the alpha, beta, and delta wolves estimate the probable location of the prey. Each solution updates its position from the prey. Linearly decreasing parameter $\vec{a}$ is reduced from 2 to 0 to emphasize the exploration and exploitation phases of the search algorithm. Candidate solutions tend to diverge from prey when $|A| > 1$ and converge towards the prey when $|A| < 1$. Finally, the HGWO-GA algorithm terminates when the criteria are satisfied.

The flowchart of the HGWO-GA algorithm is presented in Fig. 4.

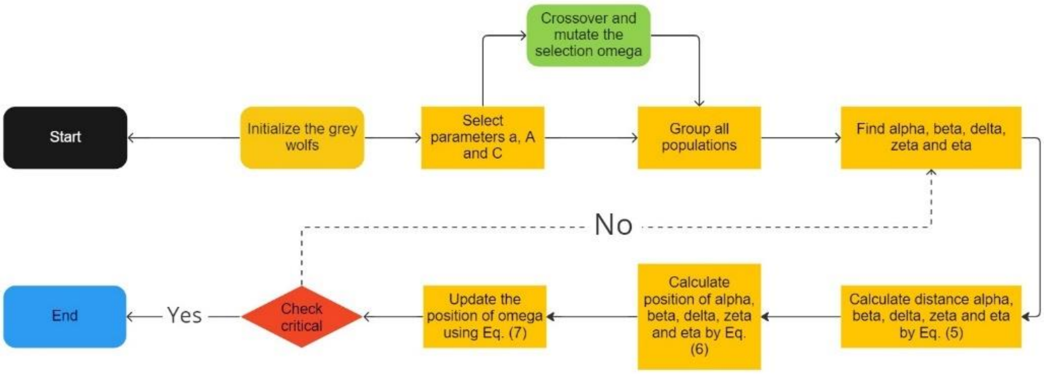


Fig. 4 – Flowchart of HGWO-GA

3 Model updating for Nam O bridge

3.1 Introduction of Nam O bridge

Nam O Bridge (see Fig. 5) is a truss bridge crossing the Cu De River in Da Nang city. The bridge was first built in 19^{th} century. Being destroyed by the war, the bridge was re-built in 2010 and is playing a vital role in connecting the North - South railway route.

Fig. 5 – Nam O Bridge

3.2 Numerical Model

To predict the structural behaviour of the bridge, a FE model is constructed using a toolbox developed on MATLAB [17]

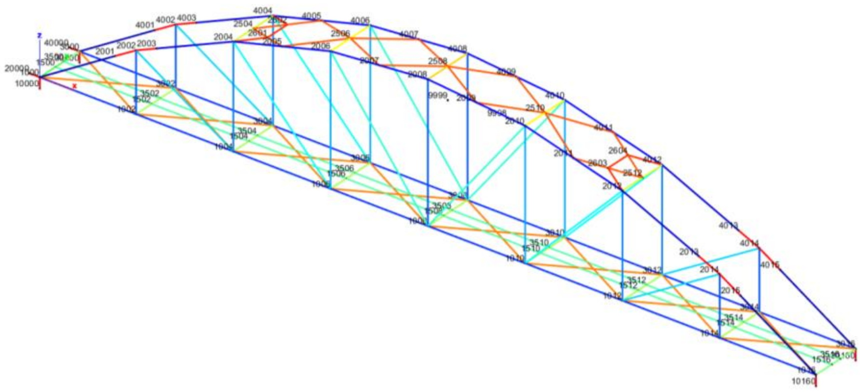


Fig. 6 – FE model of Nam O bridge

The model has 137 nodes, 156 elements, and 356 Degrees of Freedom (DOFs). Truss members consist of upper chords, lower chords, vertical chords, diagonal chords, stringers, upper wind bracings, lower wind bracings, and struts as shown inTable 1.

Table 1 – Cross-sectional properties of truss members

Members	Lower chord	Upper chord	Diagonal chord	Vertical chord	Upper wind bracing	Lower wind bracing	Stringer	Transverse Beam	Strut
Area (m^2)	0.020	0.056	0.014	0.010	0.0036	0.0049	0.020	0.026	0.020
Moment of Inertia I_y (m^4)	6.30×10^{-04}	3.1×10^{-03}	2.78×10^{-04}	1.15×10^{-04}	1.09×10^{-05}	4.38×10^{-06}	6.27×10^{-04}	3.61×10^{-03}	2.80×10^{-03}
Moment of Inertia I_z (m^4)	2.10×10^{-04}	6.70×10^{-04}	1.24×10^{-04}	5.49×10^{-05}	8.00×10^{-06}	2.38×10^{-06}	2.07×10^{-04}	2.03×10^{-04}	6.25×10^{-04}

I_y is the moment of inertia of the strong axis (the same direction as the global Y), and I_z is the moment of inertia of the weak axis (the same direction as the global Z).

Beam elements with 6 DoFs at each node including 3 translational and rotational displacements in the x, y, and z directions are used. The X-axis is along the bridge length, the Z-axis is vertical, and the Y-axis coincides with the river flow direction. Bridge bearings and truss joints are modelled using spring elements. The material propeties of elements are summerised in Table 2.

Table 2 – Material properties

Elements	ID	Young's modulus	Poison's ratio	Volumetric mass density	Stiffness
		Gpa	μ	kg/m³	
All element	$E1$	23.00	0.3	7850	Inf

3.3 Measurements.

- Test description

The modal identification test was performed on the first span. To acquire sufficient data for the structural dynamic identification and achieve compatibility with the numerical model, ideally, all directions (translational and rotational displacements in the x, y, and z directions) of all DOFs of the bridge should be composed of in the measurement grid. However, because of the existing instrumentation and terrain difficulties, some displacement components (slaved nodes) could be used. Hence, there were 64 measured nodes in total, configured in two directions (x and y or y and z) of DOFs in which, 40 nodes were fixed, and 24 other ones were roving.

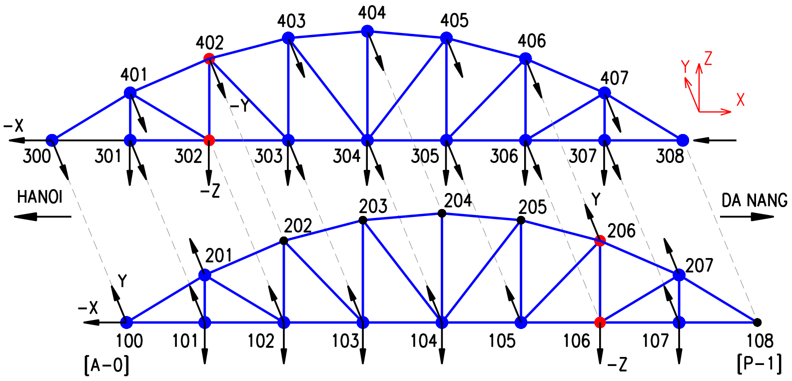


Fig. 7 – The measurement grid [12]

An overview of the measurement grid is depicted in Fig. 7 and Table 3. The red points were fixed sensors, whereas the blue ones represented the roving ones.

Table 3 – The overview of 8 setups.

Setups	Setup 1	Setup 2	Setup 3	Setup 4	Setup 5	Setup 6	Setup 7	Setup 8
Fixed channels	106*z*	106*z*	106*z*	106*z*	106*z*	106*z*	106*z*	106*z*
	206*y*	206*y*	206*y*	206*y*	206*y*	206*y*	206*y*	206*y*
	302*z*	302*z*	302*z*	302*z*	302*z*	302*z*	302*z*	302*z*
	402*y*	402*y*	402*y*	402*y*	402*y*	402*y*	402*y*	402*y*
Roving channels	101*z*	102*z*	102*y*	101*y*	102*y*	100x	403*y*	201*y*
	103*z*	104*z*	103*y*	105*y*	103*y*	100*y*	404*y*	207*y*
	301*z*	107*z*	104*y*	107*y*	104*y*	300*y*	405*y*	401*y*
	303*z*	304*z*	304y	301*y*	304*y*	300*x*	406*y*	407*y*
	305*z*	306*z*	306*y*	303*y*	306*y*	308*x*		
		307z	307*y*	305*y*	307*y*			

Ten accelerometers were used for signal acquisition. In this case, 4 sensors played a role as reference sensors, and the remaining ones were roving. The division of sensors into "reference" and "roving" is necessary when the number of available sensors is less than the number of DOFs that need to be measured. It is noted that the fixed sensors are located in locations with high sensitivity and most reflect the structural dynamic behavior. The location of these sensors was determined based on experience with similar structures or a preliminary FEM. In addition, the location of the fixed sensors can be determined based on the optimal sensor placement algorithms. A fixed number of sensors should be used as much as possible since it not only shortens the field operation time but also possibly increases the accuracy of the measurement results. In the case of multiple setups, the remaining roving sensors are used to cover information of other points, then connected with fixed sensors to reflect the overall behaviour of the structure.

Accelerometer (PCB-393B12) sensors with high sensitivity from 965 to 1,083 mV/m/s^2 were used for signal collection. It is noted that the sensitivity of these sensors needs to be carefully evaluated because this type of bridge often generates high amplitude vibration under the trainload. Therefore, the application of sensors with a too high sensitivity may lead to clipping the response or distortion. For this reason, the vibration of the bridge was only considered after a train passing.

- Data acquisition process

A 12-channel data acquisition system with 3 NI 9234 modules (Fig. 8) was used for recording voltage signals from sensors and then converting them to digital data. To control the signal acquisition system, read, and save the data, a portable computer was utilised.

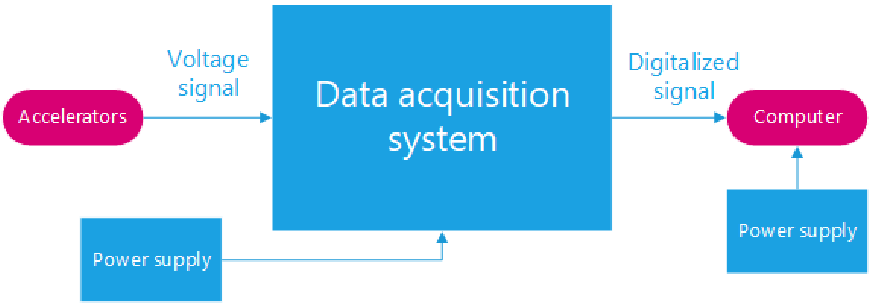


Fig. 8 – Data acquisition process

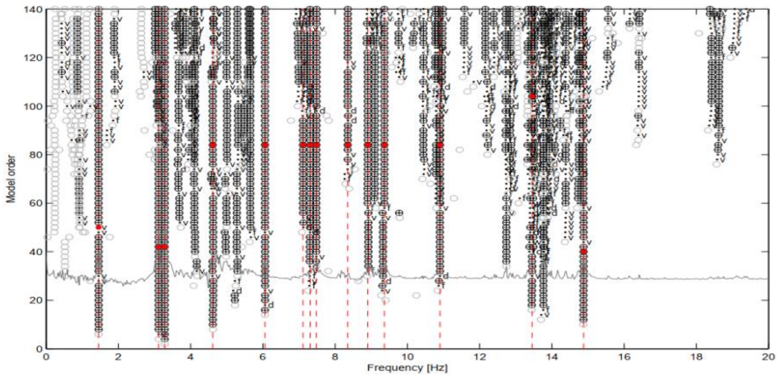
The time to complete each setup is about 10-20 minutes with a sampling frequency of 1651 Hz. Therefore, there were approximately 990.600 – 1.981.200 data points for each setup. Some setups required a shorter time depending on the movement of the train. Basically, 10 minutes are enough to collect sufficient data for structural dynamic analysis. The measurement campaign was conducted for two days shows field measurement setups.

(a)

(b)

Fig. 9 – Field measurement setups.

(a) Setup 1



(b) Setup 2

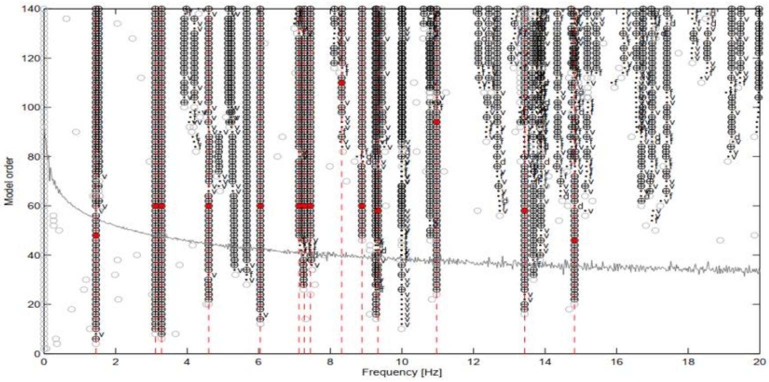


Fig. 10 - The stabilization diagram from setups 1-2

- Data pre-processing

In order to deal with measured data, Macec software [18] was employed. The process of data pre-processing consists of four main steps as follows:

First, structural geometrical features were built for visualization purposes.

Establish measured parameters including measurement units, sample frequency, amplification factors, data types, sensitivities, labels, and so on for each channel.

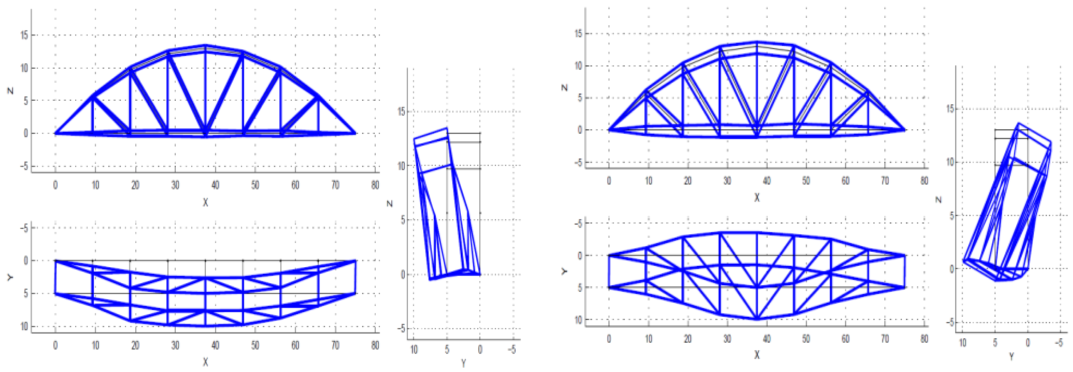
Select the appropriate frequency range for the considered structure. For this type of large-scale truss bridge, the frequency range of interest is around 0-20 Hz. Therefore, it is necessary to remove the irrelevant frequency ranges to reduce the data and facilitate System Identification (SI).

Connect measured data for the nodes including sensor positions, and measured directions.

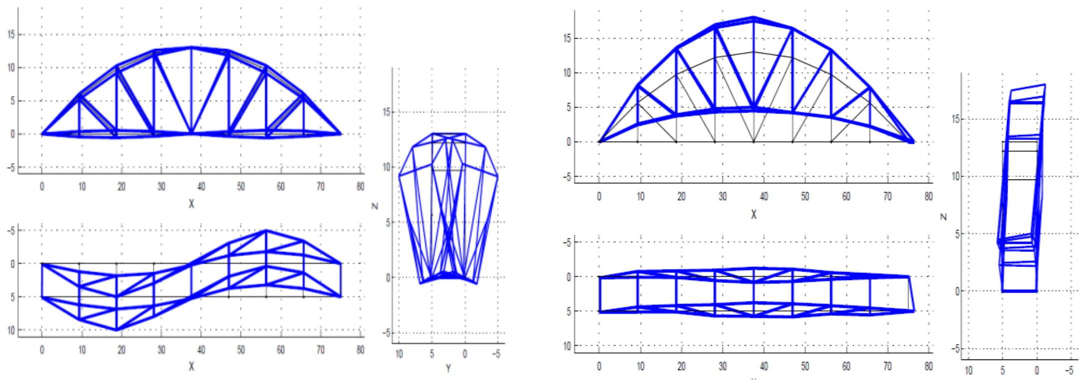
- Modal analysis

To acquire a clear stabilization diagram, some criteria need to be established. (1% of deviation for natural frequency, 1% of deviation for mode shape, 5% of deviation for damping ratio). These chosen values were derived from experience with numerous other analogous bridges. The stabilization diagrams of setups 1-2 are depicted in Fig. 10.

Structures, especially bridges, often contain multiple different vibration modes. Nevertheless, the lower vibration modes tend to play a more important role and most reflect the structural dynamic characteristics. Hence, in this work, we select the first four modes for model updating. The natural frequencies and mode shapes of the first four modes are shown in Fig. 11



Mode 1; First lateral; f=1,45 Hz   Mode 2; First torsion; f=3,11 Hz



Mode 3; Second lateral; f=3,28 Hz   Mode 4; First bending; f=4,62 Hz

Fig. 11 – Measured modes [12]

3.4 Model updating

In this section, HGWO-GA is applied for model updating of Nam O bridge. To compare with HGWO-GA, traditional GWO is also applied. The number of populations used for both algorithms is 50; coefficients of crossover and mutation are 0.7, and 0.2respectively. The objective function is the error between the calculated and measured natural frequencies and mode shapes of the first 4 modes. The upper and lower bounds of boundary condition variables are described in Table 4. These values are determined based on experience as well as other published studies [12]. The stopping condition of the algorithm is the error of the objective function is less than 10^{-7}or the maximum number of iterations is 100.

Table 4 – The upper and lower bounds of boundary condition variables

Boundary	E	$k1$	$k2$	$k3$	$k4$	$k5$	$k6$
Lower	1.9	1.0	1.0	1.0	1.0	1.0	1.0
Upper	2.2	2.0	2.0	2.0	2.0	2.0	2.0

Note: unit of $k1$,$k2$,$k3$,$k4$, is 10^{10} N/m, unit of $k5$,$k6$ is 10^7N/m, unit of E is 10^5 MPa

Fig. 12 shows the convergence of GWO and HGWO-GA. The red line represents the result of GWO, whereas the purple line indicates that of HGWO-GA. The results show that HGWO-GA has superior performance compared to the original GWO. Although the starting point of HGWO-GA is not as good as that of GWO, after 30 iterations, the convergence level of HGWO-GA surpasses that of GWO. GWO is stuck in local optimal regions, only jumping in the 5^{th} and 55^{th} iterations.It is understandable because this algorithm is crucially dependent on alpha, beta, and delta making the algorithm and does not cross and mutation operators to improve the results of the next generations.

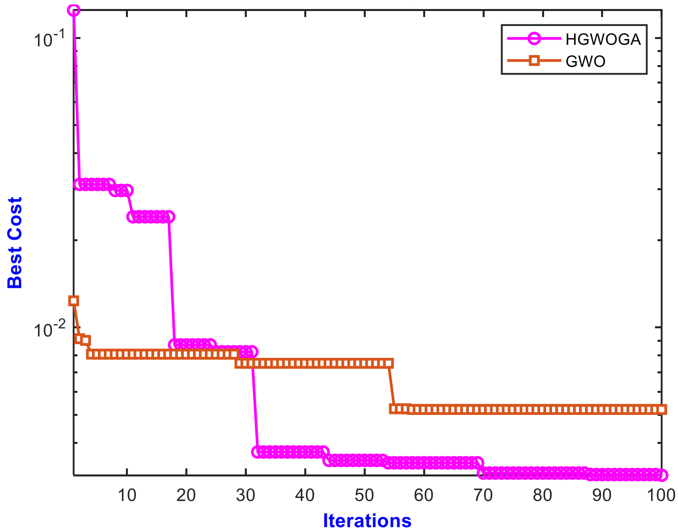


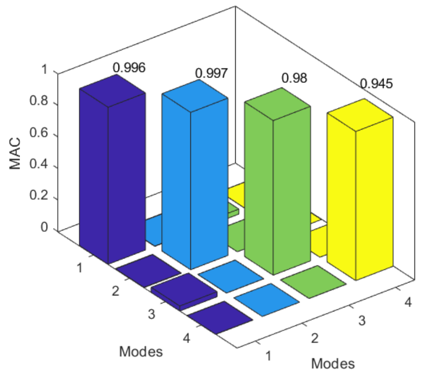
Fig. 12 – Convergence of model updating by GWO and HGWO-GA

Table 5 summarizes the results of natural frequencies before and after model updating using GWO and HGWO-GA. The errors between numerical and experimental results using GWO and HGWO-GA are 0.67% and 0.59%, respectively, which is better than the pre-updated results, 1.26%.

Table 5 – Natural frequencies before and after model updating using GWO and HGWO-GA

Mode	Frequency			
	Measurement	Before Model updating	Model updating - GWO	Model updating - HGWO-GA
	Hz	Hz	Hz	Hz
1	1.45	1.47 (1.38%)	1.45 (0.31%)	1.45 (0.30%)
2	3.11	3.06 (1.61%	3.10 (0.15%)	3.10 (0.08%)
3	3.28	3.29 (0.30%	3.28 (0.12%)	3.28 (0.02%)
4	4.62	4.7 (1.73%)	4.52 (2.08%)	4.52 (1.98%)

Fig. 13shows a good correspondence between calculated and measured mode shapes. The lowest and highest MAC values are 0.945 and 0.997, respectively. MAC calculated by HGWO-GA is better than GWO, specifically MAC of mode 4 calculated by HGWO-GA and GWO is 0.946 and 0.945, respectively.



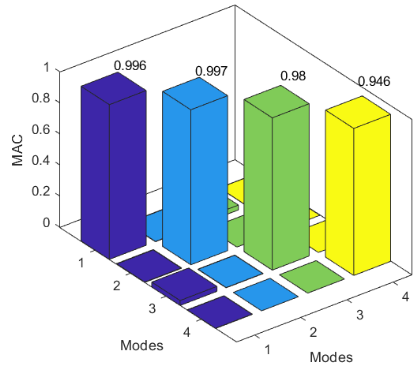


Fig. 13 – MAC values after model updating using (a) GWO, (b) HGWO-GA

Table 6 shows the stiffness of the bearings and truss joint and the elastic modulus of the truss members. After updating, the elastic modulus of the truss members decreased, while the stiffness of the bearings and truss joint remained within limits.

Table 6 – Result of variables before and after updating

	$k1$	$k2$	$k3$	$k4$	$k5$	$k6$	E
Before	1.30E+10	1.30E+10	1.30E+07	1.30E+07	1.50E+10	1.50E+10	2.00E+11
GWO	1.90E+10	1.42E+10	1.59E+07	1.03E+07	1.38E+10	1.45E+10	1.94E+11
HGWO-GA	1.49E+10	1.00E+10	1.00E+07	1.00E+07	1.30E+10	1.00E+10	1.95E+11

4 Conclusions

This paper proposes a workable solution to deal with the inverse problems of a truss bridge using a hybrid algorithm combing GWO and GA. This proposed algorithm can remedy the shortcomings of traditional GWO and generate an updated model with a high degree of accuracy. To validate the effectiveness of the proposed method, a measurement campaign was carried out on the field. For comparison, traditional GWO is also employed. From the obtained results, we have drawn the following conclusions

Both GWO and HGWO-GA provide a good agreement between numerical and experimental results.

HGWO-GA outperforms GWO in terms of accuracy not only in natural frequencies but also in MAC values.

Further investigation should be carried out to assess the efficiency of HGWO-GA to tackle optimization problems of other structures

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