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Dung Beetle Optimization Algorithm for Predicting Damage to 2D Truss Structures

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ABSTRACT

This study predicts the degree of damage in 2D truss members using the Dung Beetle Optimization algorithm (DBO) in conjunction with finite element analysis for searching natural frequencies. The difference in these natural frequencies between the finite element model and actual measurements is known as the objective function. A number of scenarios, from simple to complex, are proposed to assess the performance of this algorithm. The convergence results, which are based on MATLAB software, required only 25~30 iterations and were then displayed to validate the potential practical use of DBO. Moreover, this short study only focused on the application of DBO to predict damage of truss structures, without going into the comparison of advantages and disadvantages with other existing algorithms.

Keywords: 2D truss; Dung beetle optimization algorithm; Damage.

1.0 INTRODUCTION

Numerous real-world systems, such as forecasting, energy management, and fault diagnosis systems, contain optimization challenges that have been the subject of research for a long time. It should be noted that many complex optimization problems are extremely challenging to solve with traditional mathematical programming techniques, such as the quasi-Newton and conjugate gradient approaches. Numerous swarm intelligence (SI) optimization algorithms have been developed in this area, with the advantages of simple frameworks, self-learning capabilities, and ease of implementation. In particular, the SI system can be thought of as a swarm in which each member represents a potential solution throughout the whole search space. Furthermore, the SI system's feature is that each encounter fosters the appearance of intelligent behaviour. It is important to note that the following two steps are primarily involved in the optimization process' realization: During the iteration process, i) a group of random individuals is created within the search area, and ii) these random individuals are combined, moved, or evolved. Additionally, practically all SI-based approaches to solving optimization problems use this as their primary basis. It should be noted that the ways in which new strategies-particularly those involving combination, movement, or evolution—are designed during the optimization process vary depending on the optimization method. The dung beetle optimizer (DBO), an SI-based technique inspired by the ball-rolling, dancing, foraging, stealing, and reproduction behaviours of dung beetles, was created with the goal of offering a more effective optimizer to solve complex optimization problems, as in [1]. A dung beetle search algorithm (QHDBO) based on quantum computing and a hybrid of many strategies was developed in the study [2]. The original population of dung beetles was initialized using the good point set approach. This decreased the possibility that the algorithm would enter a local optimum solution and more equally distributed the initial population. The number of spawning and foraging dung beetles was suggested to be balanced dynamically, along with the convergence factor. As a result, the algorithm was able to concentrate on local exploration later on and global search early on. As in [3], the DBO algorithm was used with machine learning techniques to identify the best experimental circumstances for creating carbon materials with high CO_2 adsorption capability. Combining these methods could help direct the production of carbon-based materials for CO_2 adsorption. Off-grid hybrid renewable energy systems have emerged as a crucial technology for attaining sustainable development due to the quick development of renewable energy and the growing need for modernization in remote places. By adding six simple functions as convergence factors, the study [4] increased the step size of the DBO method. Six unique mathematical images were produced by combining the polar coordinate expressions of three distinct mathematical spirals and multiplying them by a zeroing factor corresponding to the number of repetitions. This improved the algorithm's dancing route and expanded the capability of global search and so on [5-10].

Besides, there are also some related documents mentioned about damage prediction for truss structures. Due to the advantages over other nondestructive methods, vibration-based damage detection systems were widely used. An enhanced Frequency Response Function indicator for identifying damage in intricate structures was introduced in the publication [7]. Various structures were employed to confirm the enhanced damage indicator's efficacy. In the initial phase, the enhanced indicator identified and located both single and numerous damages.

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Gradient-Based Optimizer, Dingo Optimization Algorithm, African Vulture Optimization Algorithm, and Artificial Gorilla Troops Optimizer were some of the recent optimization techniques used to solve the damage quantification problem after the healthy elements were removed. Known as a model-informed deep learning-based strategy, the study [8] suggested a deep learning-based damage identification method that combined data-driven and model-based techniques. In order to extract structural displacement responses from video data, this strategy initially suggested a vision-based displacement estimate method. This method increases the tracking accuracy of feature points and decreases the displacement drift brought on by traditional optical flow methods. After that, a calibrated finite element model was created in order to use time-history analysis and finite element model updating to create data sets with varying degrees of damage. A deep neural network-driven metamodel for identifying truss damage using acceleration signals that were not fully captured by a restricted number of sensors was first presented in the article [9]. This metamodel could build a superior deep neural network from previously trained, subpar ones by autonomously learning its own damage-sensitive features. The finite element method produced the data used to construct such a model. When the damage ratios of the truss members were the outputs, the acceleration behaviour corresponding to the measurement sensors were the inputs and so on [10-12].

Returning to this study, the DBO algorithm, by simulating the ball-rolling, dancing, foraging, stealing, and reproduction behaviours of dung beetles, was used to predict the damage of 2D trusses. In conjunction with the finite element analysis like [13-15] for calculating natural frequencies, the difference in these natural frequencies between the finite element model and actual measurements is known as an objective function. It can be seen that this study does not focus on comparing the DBO algorithm with other swarm optimization algorithms but only applies it in solving a specific problem based on building several scenarios from simple to complex for verification. Therefore, the specific evaluation of the advantages and disadvantages of this algorithm compared to other algorithms is not obviously presented here. The convergence results, which are based on MATLAB software, are displayed to validate the potential practical use. This research's subsequent sections are as follows: Part 2 provides methodology. Part 3 displays the results and discussion, and the final section offers some remarks.

2.0 METHODOLOGY

As a common bug in nature, the dung beetle is known to consume animal feces. It should be noted that dung beetles are widespread throughout the world and play a crucial role in the environment as natural decomposers. According to research, dung beetles have an intriguing habit of rolling out their feces after forming it into a ball, as seen in Fig. 1. It is important to note that dung beetles move their dung ball as fast and effectively as possible in order to avoid competition from other dung beetles. However, dung beetles have an interesting ability to navigate and make the dung ball move in a straight course by using astronomical cues, particularly the sun, moon, and polarized light. However, the dung beetle's path becomes bent and occasionally even slightly round if there is no light source present at all. More of their characteristics can be found in the literature [1]. The Dung Beetle Optimization (DBO) algorithm was also proposed in [1], and it was primarily inspired by the rolling, jumping, foraging, thieving, and reproductive actions of dung beetles.

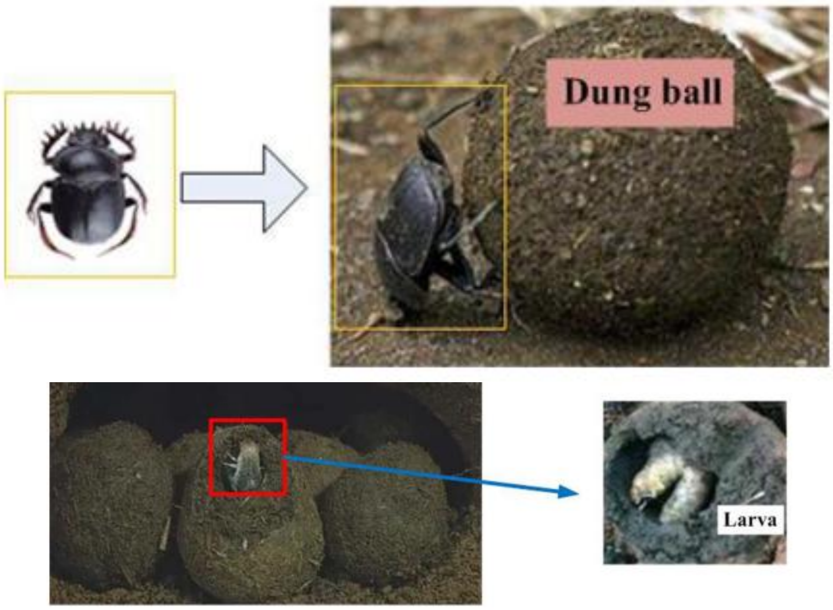

Figure 1. The behaviour of the dung beetle [1]

The literature [1] stated that the ball-rolling dung beetle's position has been updated and can be written as

$$x_i(t+1) = x_i(t) + \alpha \times k \times x_i(t-1) + b \times \Delta x \tag{1}$$

$$\Delta x = \left| x_i(t) - X^w \right| \tag{2}$$

in which t represents the current iteration number, $x_i(t)$ denotes the position information of the ith dung beetle at the tth iteration, $k \in (0, 0.2]$ denotes a constant value which indicates the deflection coefficient, b indicates a constant value belonging to (0, 1), α is a natural coefficient which is assigned -1 or 1, X^w indicates the global worst position, and Δx is used to simulate changes of light intensity. The three accompanying notes can be followed as in [1], so the author does not go into detail here.

3.0 RESULTS AND DISCUSSION

A truss structure with the required data is provided for examination in order to confirm the applicability of DBO, as seen in Figure 2 and Tables 1 and 2. The objective function is the difference in natural frequencies between the finite element model and the actual measurements. The change in the structure's stiffness is used to evaluate DBO. The location of the damage is therefore predicted. To verify accuracy, Table 3 presents three damage scenarios, and Figure 3 illustrates the second damage scenario.

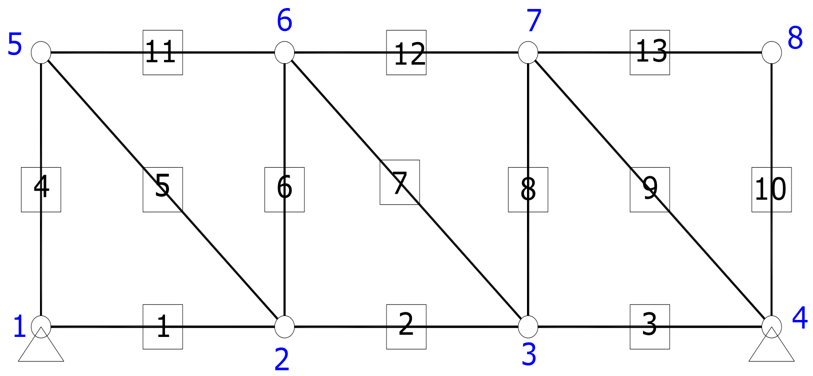

Figure 2. The 2D truss structure

Table 1: The coordinates of nodes

Node	X(m)	Y(m)	Node	X(m)	Y(m)
1	*0*	*0*	**5**	*0*	*2*
2	*2*	*0*	**6**	*2*	*2*
3	*4*	*0*	**7**	*4*	*2*
4	*6*	*0*	**8**	*6*	*2*

Table 2: The properties of truss structure

E	205 GPa
ρ	7850 kg/m^3
A	7.0686 cm^2

Table 3: The three damage scenarios

Scenarios	Damage bar(s)	Severity of damage
The first scenario	Bar 7	35%
The second scenario	Bar 3	30%
	Bar 5	20%
The third scenario	Bar 1	35%
	Bar 8	25%
	Bar 13	20%

The findings, which are shown in Figures 4 to 6, showed that DBO yields the intended results for damage structure prediction. Additionally, it is evident that the DBO algorithm requires only 25~30 iterations to get the intended results. With five different updating rules related to the ball-rolling, dancing, foraging, stealing, and reproduction behaviours of dung beetles, the DBO algorithm helps find good results. Besides, by using this stronger searching ability, the DBO algorithm has avoided getting stuck in local optima quite well.

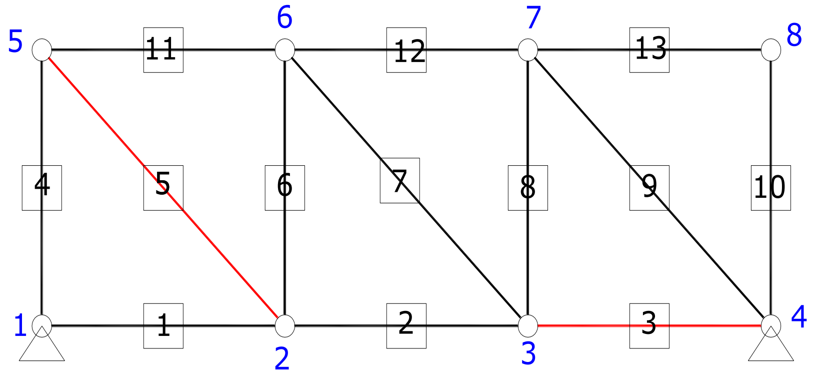

Figure 3. The illustrated of the second damage scenario

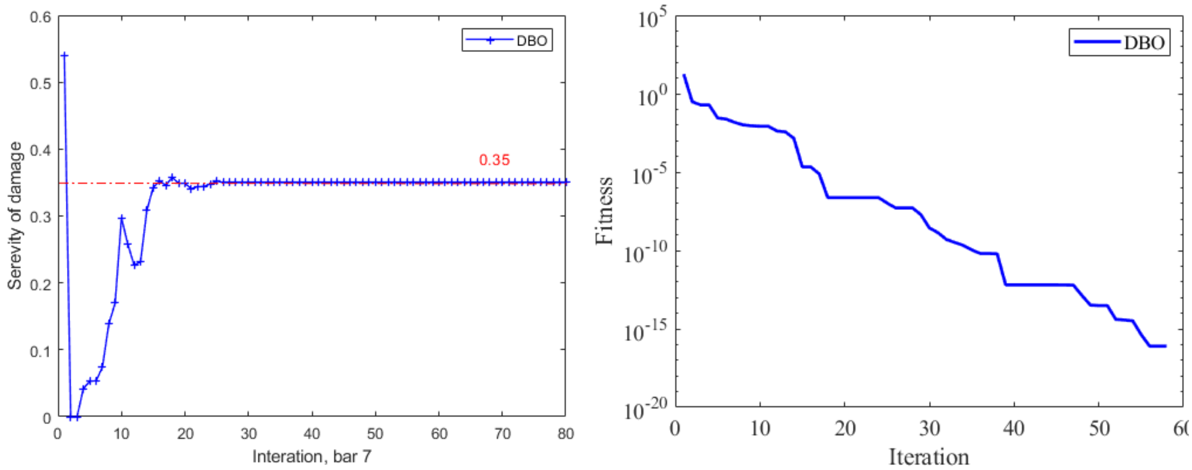

Figure 4. Describe the convergence for the first damage scenario

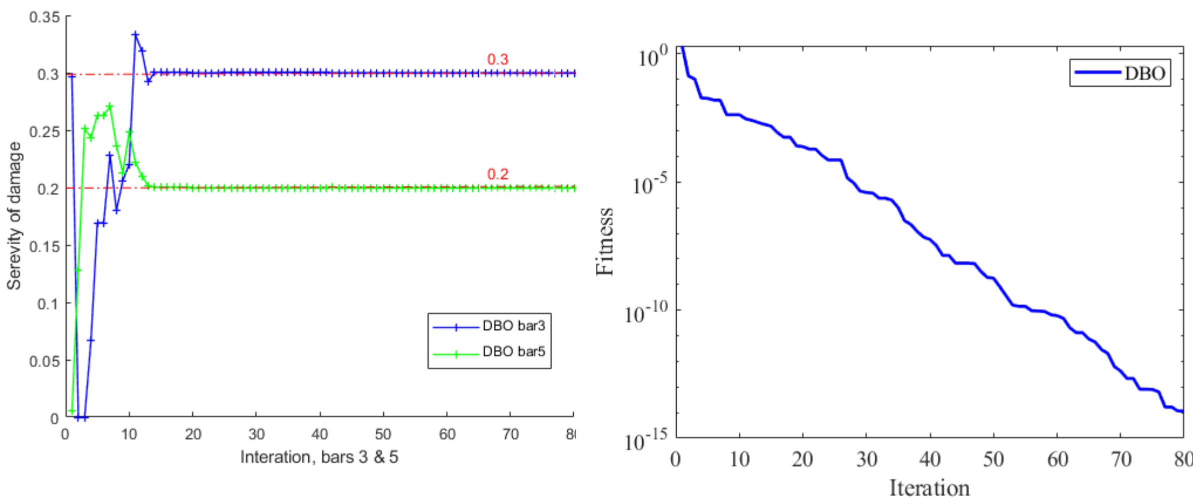

Figure 5. Describe the convergence for the second damage scenario

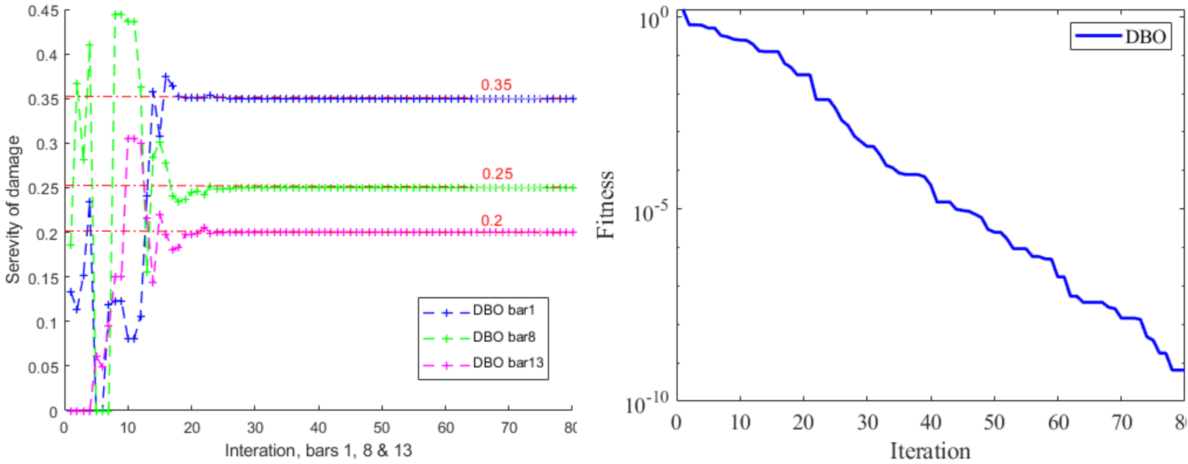

Figure 6. Describe the convergence for the third damage scenario

It can be seen that the DBO algorithm has identifed the potentially damaged location in all cases. The convergence curve showed that the performance of this algorithm is good. On the other hand, for the third case, the complexity of the problem led to more challenges for all algorithms, but DBO still showed excellence in overcoming this difficulty in just about 30 iterations.

4.0 CONCLUSION

This study presents how to use the DBO algorithm to detect damage in 2D truss structures. A number of scenarios, from simple to complex, are proposed to assess the performance of this algorithm. The convergence results show how well the DBO algorithm predicts the location and magnitude of damage.

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DECLARATION OF COMPETING OF INTEREST

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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