An improved Artificial Rabbit Optimization Algorithm using neural network for damage detection of truss bridge

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Abstract

This research proposes an improved Artificial Rabbit Optimization Algorithm (ARO) for damage detection of truss structures. The proposed method utilizes paralleling vectorized data and combines it with an Artificial Neural Network (ANN) to improve the accuracy and efficiency of the damage detection process. The method aims to address the limitations of existing methods that suffer from slow convergence and low accuracy due to the high-dimensional search space and the presence of noise in the data. To evaluate the effectiveness of the proposed method, numerical experiments were conducted on a truss structure with multiple damage scenarios. The results demonstrate that the proposed method outperforms existing methods in terms of accuracy and computational cost. The proposed method provides a promising approach for damage detection in truss structures, and its effectiveness has been demonstrated through numerical experiments. Overall, the proposed method provides a significant improvement over existing methods and can be a valuable tool for structural health monitoring and damage detection in truss structures.

Keywords: Artificial Rabbit Optimization Algorithm, vectorized data, Artificial Neural Network, damage detection, truss structure

Objectives

- This research aims to improve the working capability of the original ARO optimization algorithm in terms of accuracy and computational cost.
- The use of of Artificial Neural Network - ANN has been proven in literature to help solving complex problems with much less computational cost, thus the research aims to improve the algorithm including ANN to solve structural damage identification problems with high efficacy level.

Methodology

Artificial Rabbit optimization

The Artificial Rabbit Optimization(ARO) was introduced by Wang et al [1] in July 2022. The algorithm is Inspired by the feeding and hiding behavior of rabbits, which consists of two behaviors:

Behavior 1: Divergent Feeding (exploration)

Behavior 2: Random Hiding (exploitation)

[1] Wang, Liying, et al. "Artificial rabbits optimization: A new bio-inspired meta-heuristic algorithm for solving engineering optimization problems." Engineering Applications of Artificial Intelligence 114 (2022): 105082.

+ Behavior 1: Divergent Feeding (exploration)

Rabbits will only forage for food away from their burrow to avoid other predators. A mathematical model is suggested:

$$v^{\leftrightarrow}i(t+1) = x^{\leftrightarrow}j(t) + R\cdot(x^{\leftrightarrow}i(t) - x^{\leftrightarrow}j(t)) + round(0.5\cdot(0.05 + r1))\cdot n1$$

Where: $v^{\leftrightarrow}i(t+1)$ is the candidate position of the ith rabbit at the time (t+1); R represents the running; $r1$,$n1$: random parameters (0,1); L is movement pace of rabbit.

+ Behavior 2: Random Hiding (exploitation)

Rabbits will create disturbances for predators by digging several other similar burrows. After the rabbit survives after both two phases searching for food and hiding randomly from danger. The position of the ith rabbit is:

$$\vec{x}_i(t+1) = \begin{cases} \vec{x_i}(t) & f(\vec{x_i}(t)) \le f(\vec{v_i}(t+1)) \\ \vec{v}_i(t+1) & f(\vec{x_i}(t)) > f(\vec{v_i}(t+1)) \end{cases}$$

Exploration and Exploitation switch

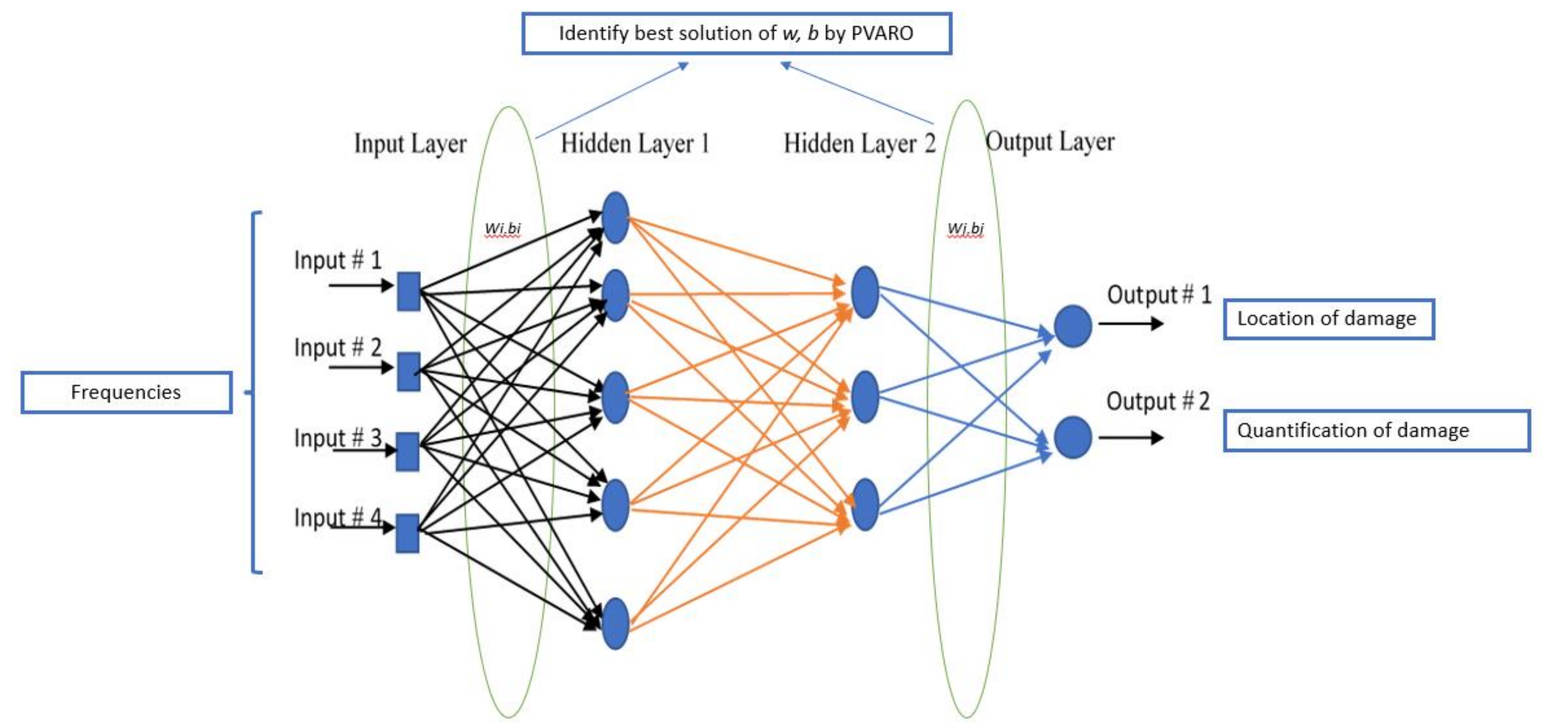
Phase determination based on energy shrink factor A: $A(t) = 4\left(1-\frac{t}{T}\right)\ln\frac{1}{r}$

Where *r is random between [0,1];* exploration occurs when A(t)>1, while exploitation happens when A(t)≤1.

Improved Artificial Rabbit Optimization (ANNPVARO)

- Vectorization and parallel of data and parameters is introduced to the original optimization. Combination with ANN to optimize weight value of ANN.
- The best solutions (training parameters) are determined and converted to weight and bias values of ANN used to train the network.

$$mse = \frac{1}{N}\sum_{i=1}^{N}(e_i)^2 = \frac{1}{N}\sum_{i=1}^{N}(t_i - y_i)^2$$



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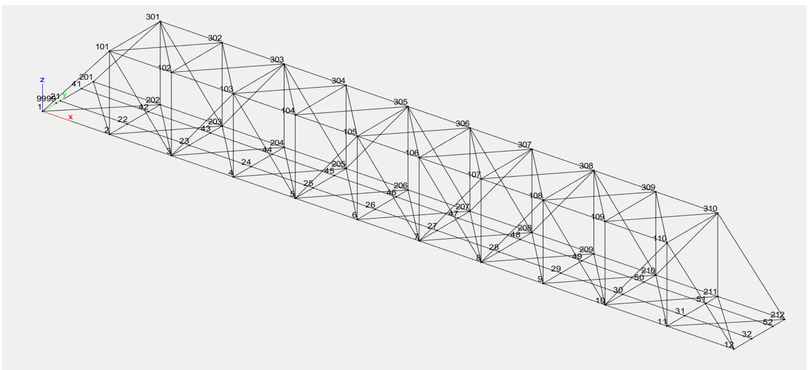
Case study validation

- ANNPVARO is applied to solve damage detection problems of Chuong Duong bridge, which is a lifeline truss bridge in Vietnam. Measurement on truss span number 10, L = 89.28m. Baseline FE model of the bridge is generated [2]

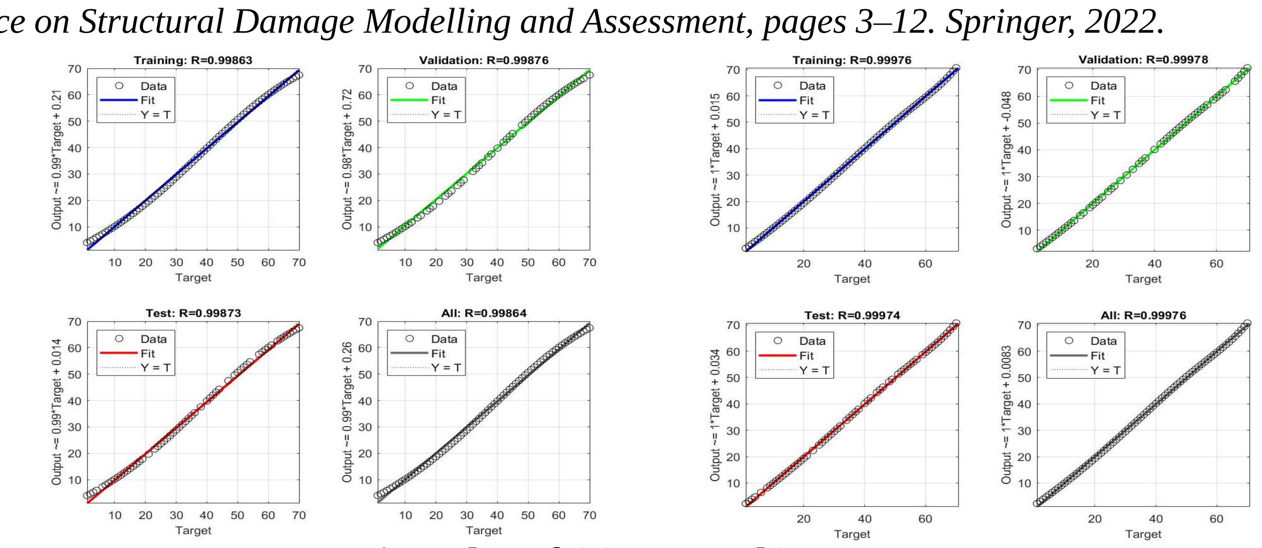


Baseline FE model of the bridge span

Mode number	Frequencies (Hz)	Mode type
1	1.75	Vertical bending
2	3.45	Torsion
3	4.30	Vertical bending
4	4.90	Lateral movement
5	5.34	Lateral bending

Modal properties of the baseline FE model

[2] Lan Ngoc-Nguyen, Samir Khatir, Hoa Ngoc-Tran, Hieu Nguyen-Tran, Binh Duc-Nguyen, Thanh Bui-Tien, and Magd Abdel Wahab. Finite element model updating of lifeline truss bridge using vibration-based measurement data and balancing composite motion optimization. In Proceedings of the 2nd International Conference on Structural Damage Modelling and Assessment, pages 3–12. Springer, 2022.

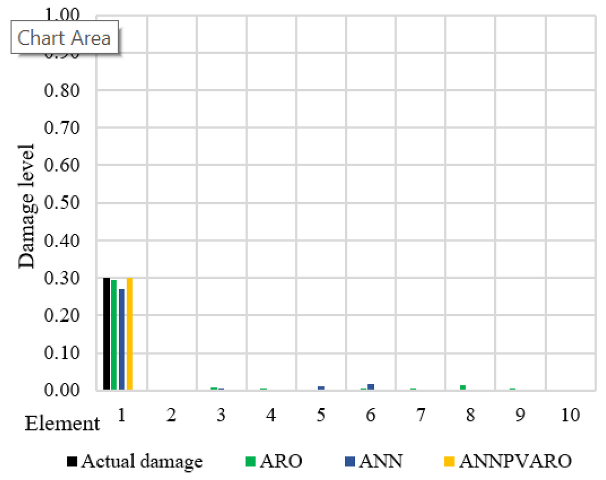


Regression plot of (a) ANN; (b) ANNPVARO

Input data: natural frequencies of the first 05 modes of different damage scenarios
Damage generated by reducing element’s stiffness from 0-70% with 1% interval
Total number of input data: 700 samples
Samples used for training, validation and test: 70%, 15% and 15% of total samples
Input: natural frequencies, output: location + quantification of damage

Method	MSE value	R value	Computational cost (s)
ARO			295s
ANN	1.21	0.99864	3.17
ANNPVARO	0.05	0.99976	69.2

⇒ **ANNPVARO has better R value and MSE value than ANN (0.99976 vs 0.99864 and 0.05 vs 1.21)**
⇒ **ANNPVARO has better accuracy than traditional ANN**
⇒ **Computational cost is much better than the original ARO (69.2s vs 295s), with slightly higher level of accuracy**



Damage detection of element number 1 with 30% damage induced for the three methods

Conclusion and Future work

- In this study, we proposed an enhanced version of ARO using ANN and evaluated its ability to locate and quantify single damages on a bridge structure. Our results showed that ANNPVARO outperformed ANN in terms of regression and mean squared error values. Additionally, ANNPVARO demonstrated significantly better computational efficiency than ARO. These findings suggest that the proposed method using ANNPVARO is effective for detecting and quantifying single damages on bridge structures. Future research could explore the use of this method in more complex structural systems to further validate its efficacy. Overall, the results of this study provide valuable insights for the development of efficient and accurate structural damage detection methods.