APPLICATION OF ANTLION'S HUNTING STRATEGY AND ARTIFICIAL NEURAL NETWORK TO FAILURE IDENTIFICATION OF 2D CANTILEVER STRUCTURES

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The aims of the study

- Improving ANN's performance by a stochastic optimization process
- Proposing a simple and effective tool for damage detection in 2D structures using mode shapes and their derivatives

Problems

- Assessment of structural damage is always an essential requirement in maintenance and repair of existing structures.
- Visual inspection cannot sufficiently satisfy this requirement → Using dynamic properties for a direct localization of damage via damage index but **NO** quantification.
- Optimization process or artificial neural network can be used to deal with damage quantification. **HOWEVER,** the first approach is time-consuming. The latter is fast **BUT** can be trapped in local minima → Taking advantage of the two approaches to **PROPOSE** a hybrid model, ALO[1]-ANN

[1]S. Mirjalili, "The Ant Lion Optimizer," *Advances in Engineering Software*, vol. 83, pp. 80–98, May 2015, doi: 10.1016/j.advengsoft.2015.01.010

Case studies

Two cantilever structures

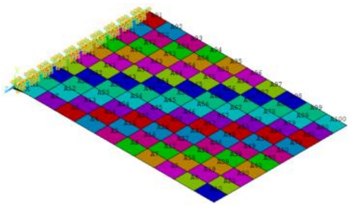

Fig1. Two damaged elements /100 elements in a pure plate

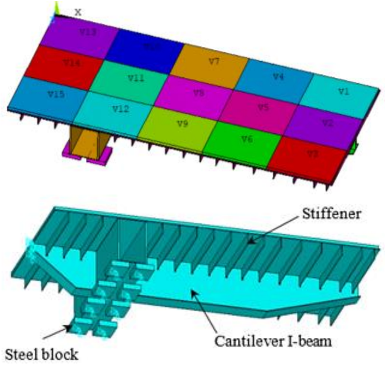

Fig2. One damaged element/15 elements in a concrete-steel composite structure

Methodology of the proposed method

1. Mode shape derivative based damage identification index, MSDBDI[2]:

$$MSDBDI_k = \frac{\sum_{j=1}^{nm}\left\{\left|\left(\left|\Delta\kappa\right|\times\Delta\phi^2\right)-\left(\Delta\theta^2\times\Delta\phi\right)\right|\times\Delta\kappa\right\}}{nm} \quad (1)$$

$$MSDBDInor_k = \max\left[0,\left(\frac{MSDBDI_k - mean(MSDBDI)}{std(MSDBDI)}\right)\right] \quad (2)$$

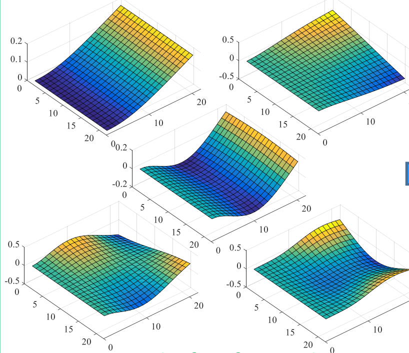

Fig3. The first five modes

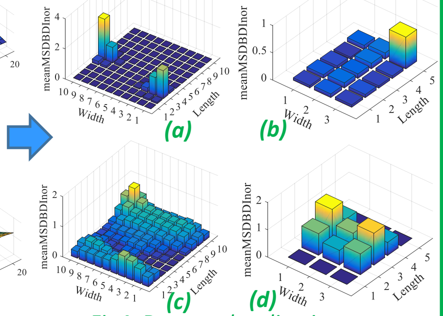

Fig4. Damage localization

[2]N. Navabian *et al.* (2016), "Damage identification in plate-like structure using mode shape derivatives," *Arch Appl Mech*, vol. 86, no. 5, pp. 819–830

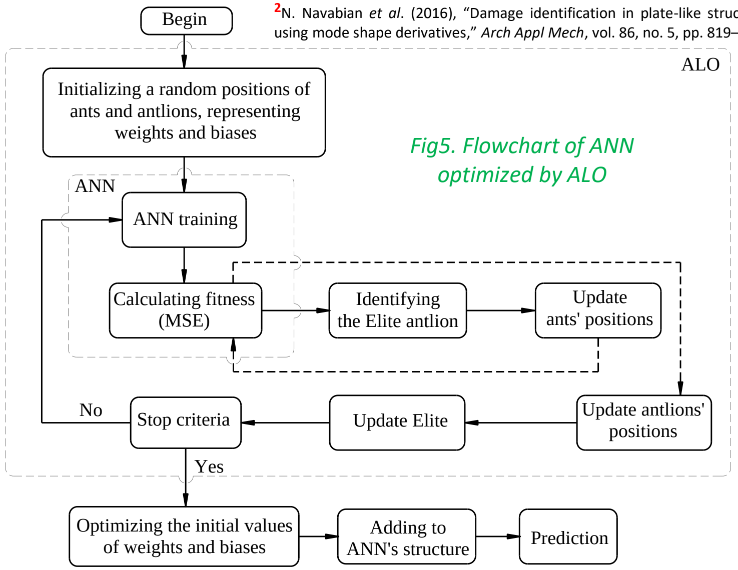

Fig5. Flowchart of ANN optimized by ALO

Results of using ALOANN

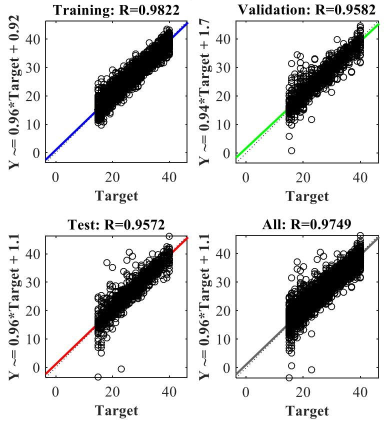

Fig6. Regression plots of CS1

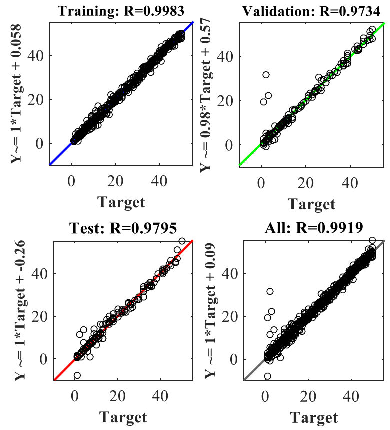

Fig7. Regression plots of CS2

Summary

CS	*Damaged element(s)*	*Stiffness reduction*	*Investigated elements*
CS1	2	15%-40%	15th-35th
CS2	1	1%-50%	1st-12th

CS	*Samples*	*ANN's structure*	*Data split*
CS1	5460	50-30-3	70-15-15
CS2	600	15-31-2	70-15-15

Conclusions

- ALOANN could obtain high R-values with all data, 0.975 for CS1 and 0.992 for CS2 compared to 0.970 and 0.99 using ANN
- In CS1: ALOANN localized correctly all damage scenarios while ANN misidentified one. The errors between estimated and actual levels using ALOANN were smaller than that of ANN.
- In CS2: ALOANN and ANN were successful in damage localization for all scenarios. However, in almost all cases, ALOANN showed superior performances in damage quantification compared to ANN
- Parallel working should be considered in further works to reduce computational time.

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