Journal of Zhejiang University-SCIENCE A

Cite this as: Long Viet Ho, Duong Huong Nguyen, Guido de Roeck, Thanh Bui-Tien, Magd Abdel Wahab, 2021. Damage detection in steel plates using feed-forward neural network coupled with hybrid particle swarm optimization and gravitational search algorithm. *Journal of Zhejiang University-SCIENCE A (Applied Physics & Engineering)*, 22(6):467-480. https://doi.org/10.1631/jzus.A2000316

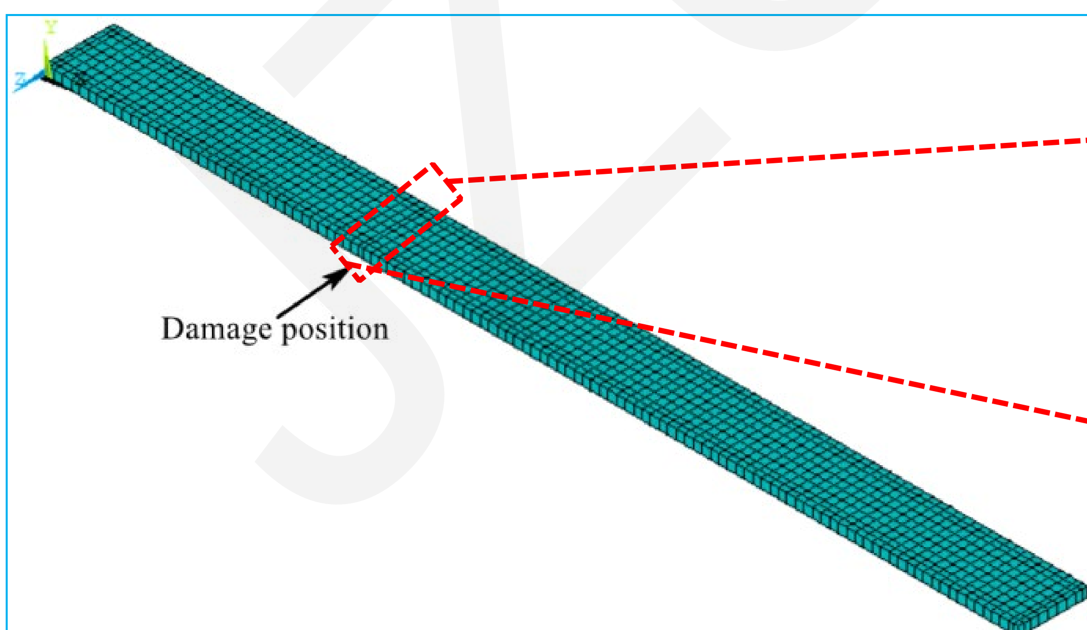
Damage detection in steel plates using feed-forward neural network coupled with hybrid particle swarm optimization and gravitational search algorithm

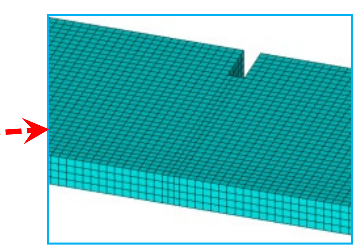
Key words:

FNN-PSOGSA, Modal damage indices, Damage detection, PSO, GSA, Hybrid algorithm PSOGSA

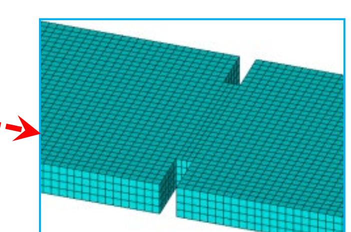
The aim and objective

- This study aims to build a simple, effective assessment tool for structural health monitoring using flexibility method. $F = \left(\sum_{i=1}^{n} \frac{1}{\omega_i^2} . \phi_i . \phi_i^T \right) \Rightarrow \Delta = F_{\text{intact}} - \text{F}_{\text{damaged}} \Rightarrow \overline{\delta}_j = \max_i \left| \Delta_{i,j} \right|$
- The objective of the study is a steel plate. Changes in modal properties are caused by real cuts instead of stiffness reduction assumption.
- Numerical studies are used to assess the effectiveness of this tool.
  - *Several damage scenarios with severity from 1% to 40% with an interval of 1% are used for training, test.*
  - *Two extra scenarios with damage severity at 17.24% and 34.76% are used for verification.*





One cut, severity 17.24%



Two cuts, severitfy 34.76%

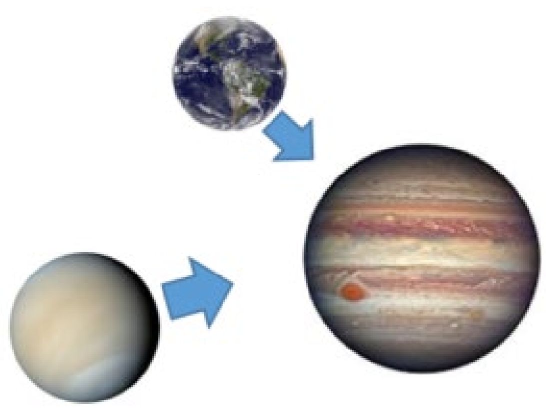
Simulation of steel beam in ANSYS

Cuts on the beam

Methodology

Hybrid Particle Swarm Optimization and Gravitational Search Algorithm (PSOGSA)

Inspirations

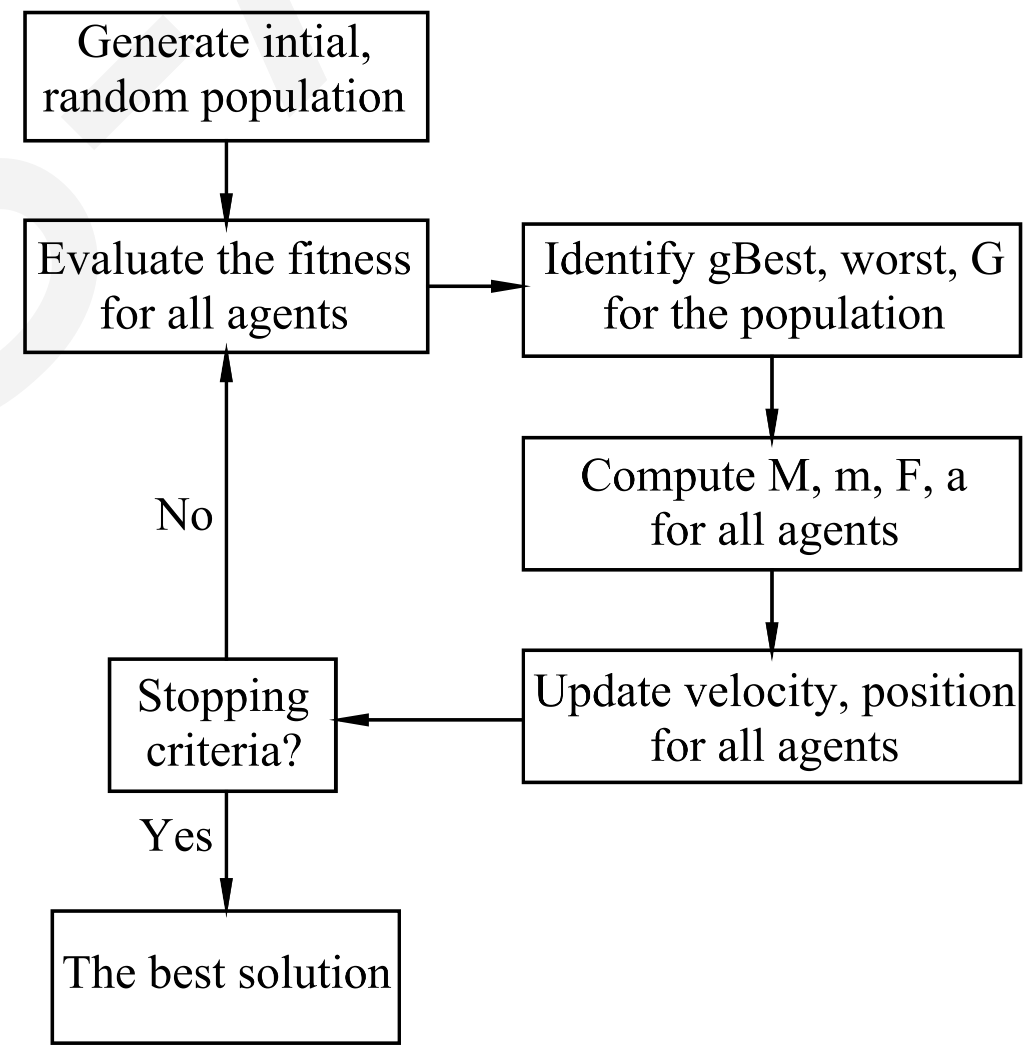


Local search capability

Social thinking

+ ↑ the exploration of PSO

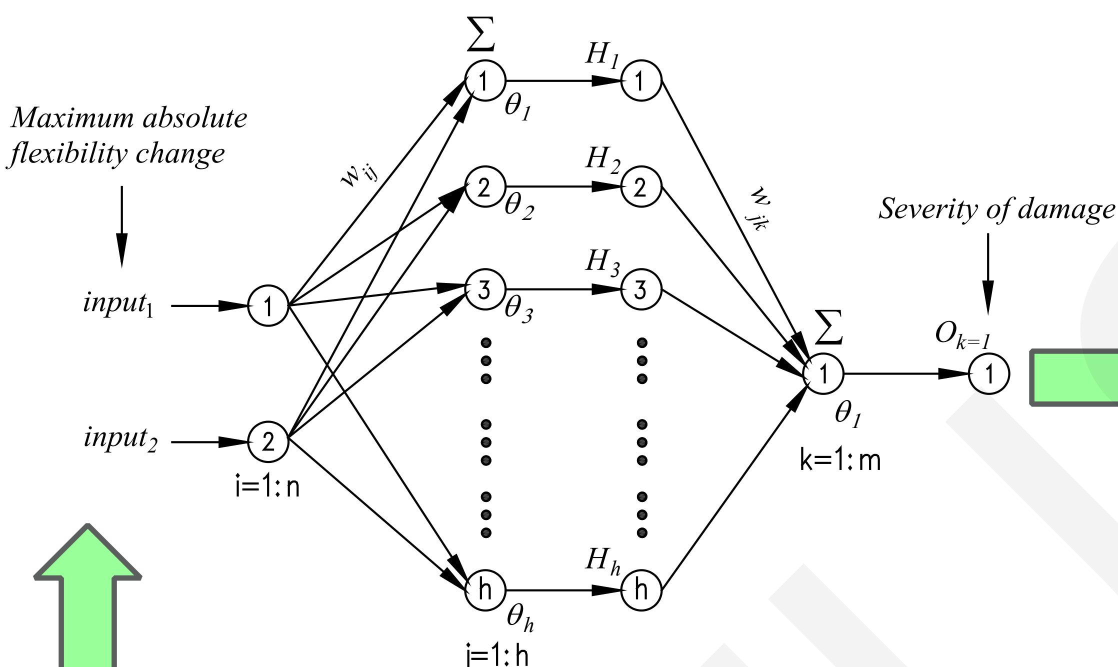
+ ↑ the exploitation of GSA



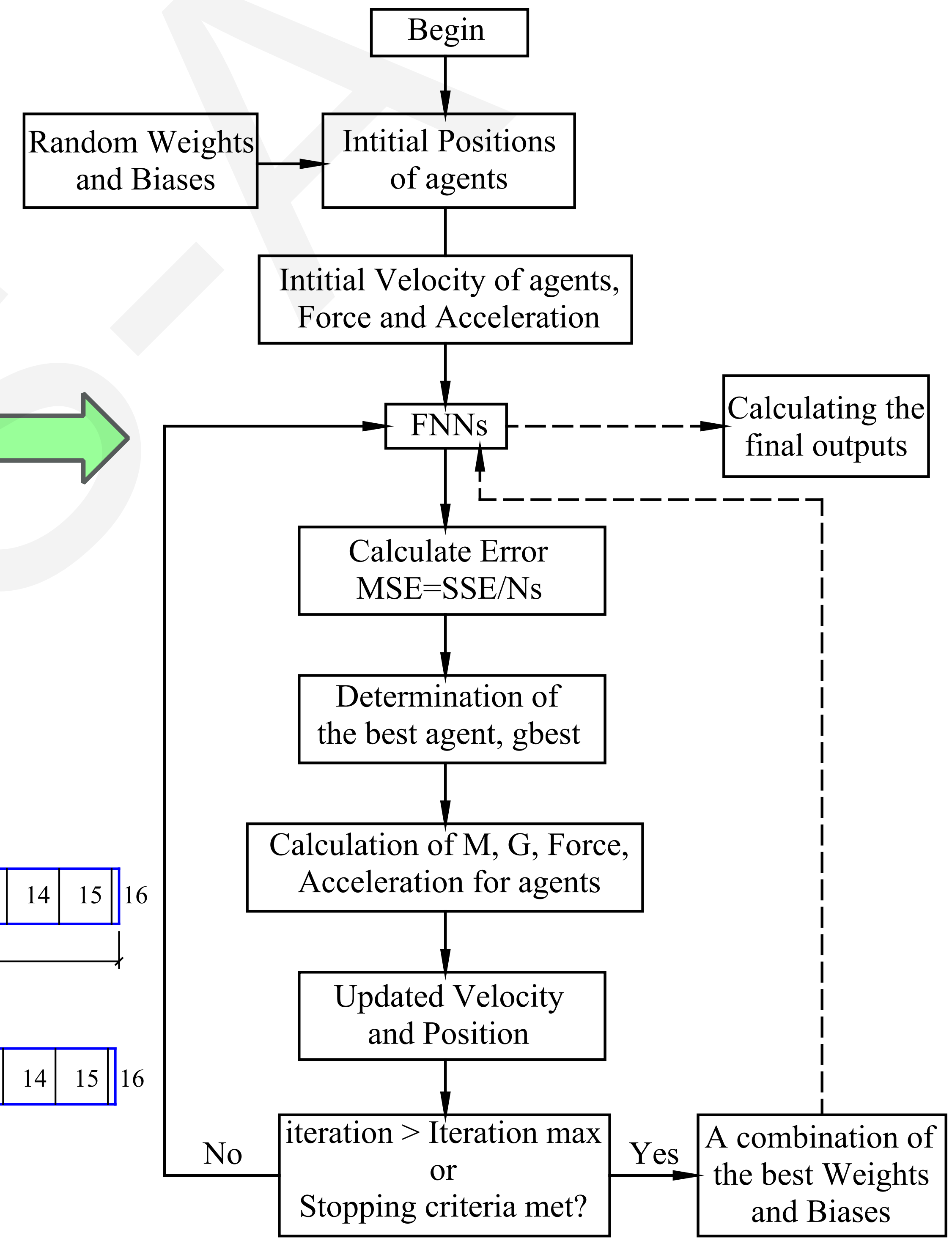
Flowchart of PSOGSA

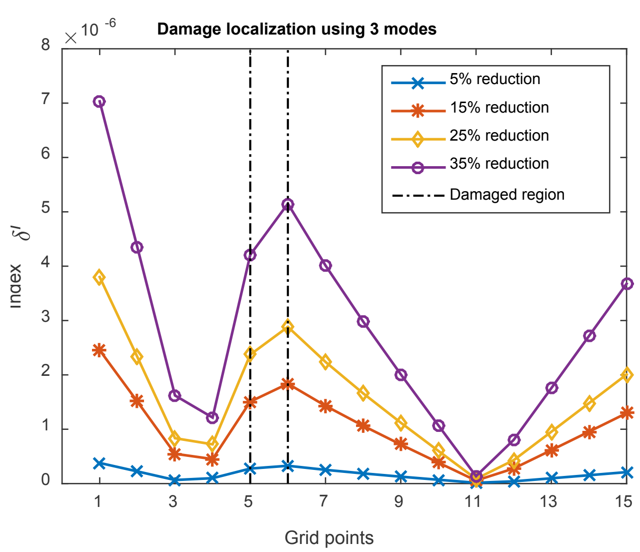
Methodology

Working procedure of FNNPSOGSA

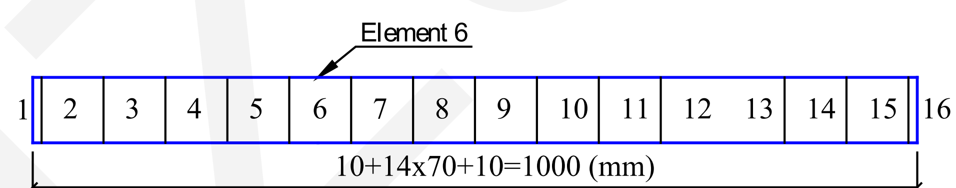


Architecture of Feedforward neural network for damage detection

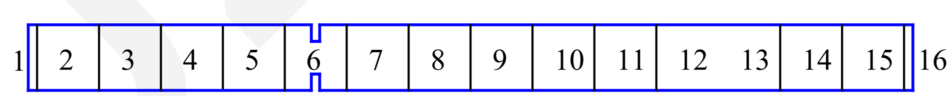




Calculating damage index to localize damage position



Intact beam



Damaged beam with real cuts

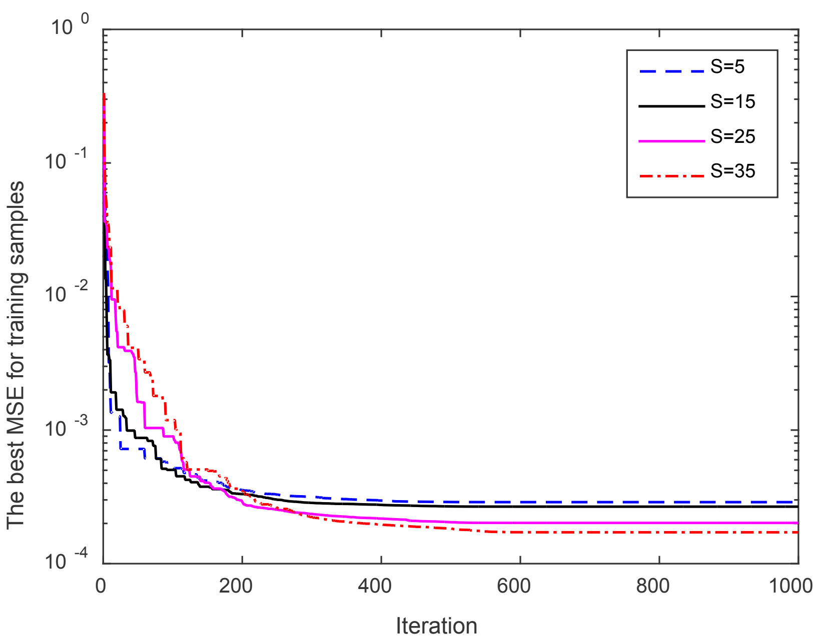
← *Modal properties of intact and damaged beam*

Collecting data for training, test

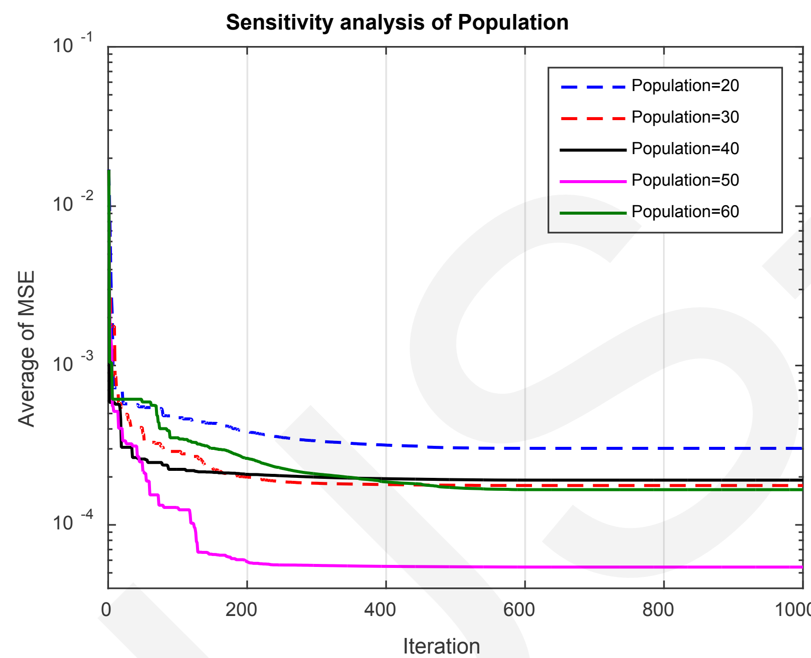
Flowchart of FNNs improved by PSOGSA

Results

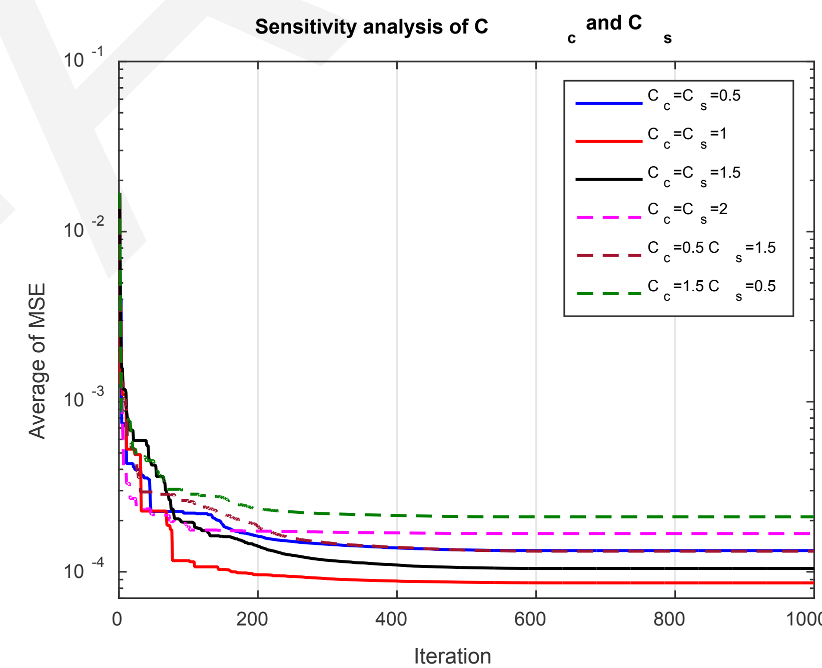
1. Sensitivity analysis of hyper-parameters for FNN and PSOGSA



Convergence curves of FNNPSOGSA associated with variation of number of hidden nodes



Convergence curves of variation of population with c_c=c_s=1



Convergence curves of variation of c_c, c_s with population = 50

The best SSE and the best MSE of FNNPSOGSA over 1000 iterations

Number of hidden nodes (S)	SSE $\times 10^{-2}$	MSE $\times 10^{-4}$
5	1.15	2.89
15	1.07	2.67
25	0.807	2.02
35	**0.687**	**1.72**

The standard deviation, best and average MSE over 20 runs associated with different populations

Value	Average MSE	The best MSE	Std MSE
Population = 20	3.02×10^{-4}	1.38×10^{-4}	4.99×10^{-4}
Population = 30	1.77×10^{-4}	1.60×10^{-4}	1.94×10^{-5}
Population = 40	1.91×10^{-4}	1.03×10^{-4}	6.60×10^{-5}
Population = 50	$\mathbf{5.43\times10^{-5}}$	4.89×10^{-5}	$\mathbf{4.73\times10^{-6}}$
Population = 60	1.66×10^{-4}	$\mathbf{4.72\times10^{-5}}$	3.29×10^{-4}

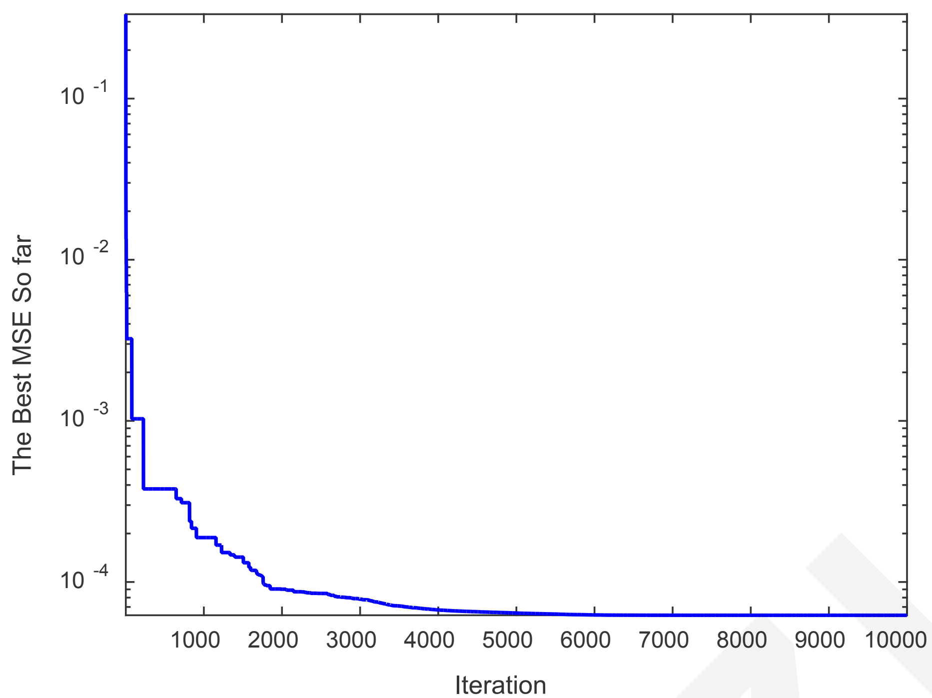
The standard deviation, best and average MSE over 20 runs associated with different c_c, c_s.

Value	Average MSE	The best MSE	Std MSE
c_c=c_s=0.5	1.33×10^{-4}	8.01×10^{-5}	6.30×10^{-5}
c_c=c_s=1	$\mathbf{8.60\times10^{-5}}$	6.53×10^{-5}	$\mathbf{2.19\times10^{-5}}$
c_c=c_s=1.5	1.05×10^{-4}	6.46×10^{-5}	1.08×10^{-4}
c_c=c_s=2	1.68×10^{-4}	1.48×10^{-4}	2.23×10^{-5}
c_c=0.5 c_s=1.5	1.32×10^{-4}	$\mathbf{5.46\times10^{-5}}$	1.30×10^{-4}
c_c=1.5 c_s=0.5	2.10×10^{-4}	1.58×10^{-4}	7.37×10^{-5}

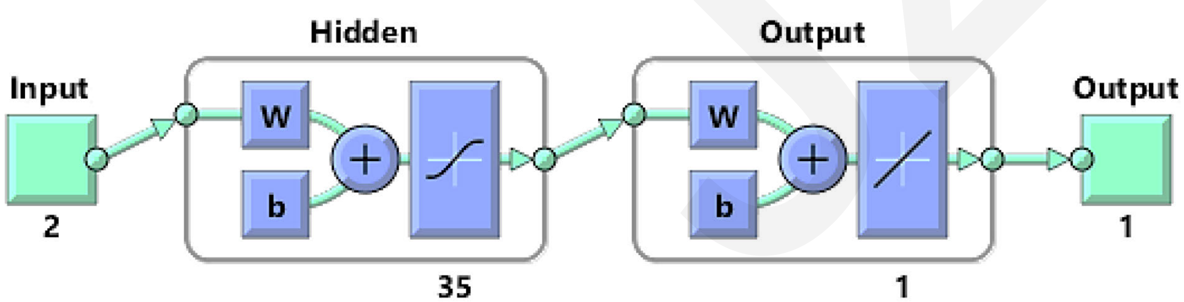
→ Choosing hyper-parameters: Hidden nodes S = 35, population =50, c_c=1 and c_s=1

Results

2. Damage quantification



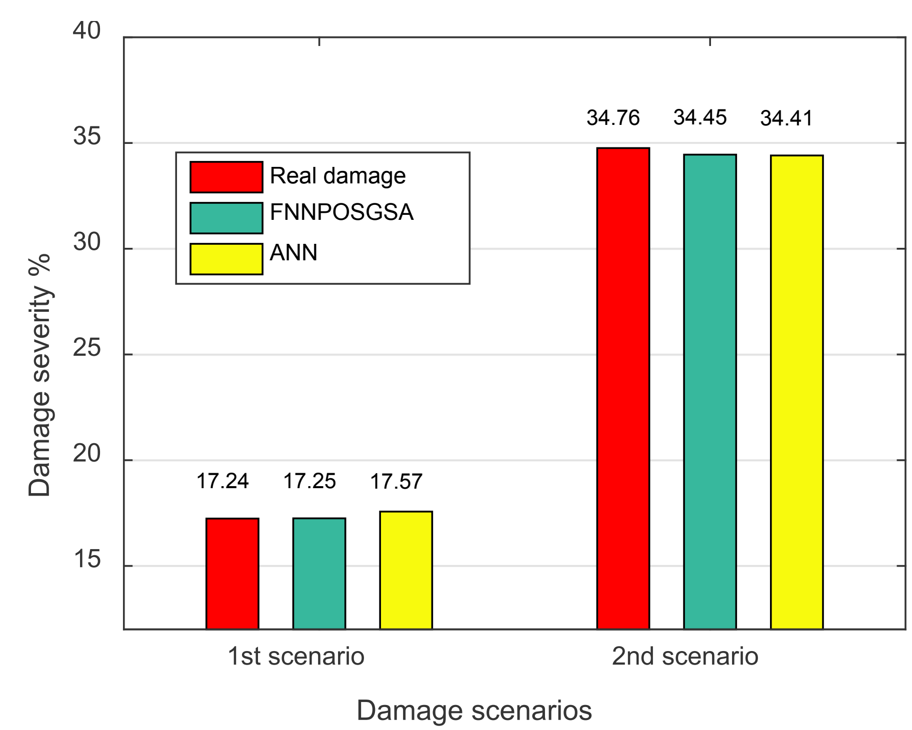
Convergence curves of FNNPSOGSA with number of hidden nodes S = 35 over 10 000 iterations.



Architecture of conventional ANN, 2-35-1

Comparison of damage severity estimated by FNNPSOGSA and ANN

Damage Scenario	Real damage (%)	FNNPSOGSA (%)	Error (%)	ANN (%)	Error (%)
1	17.24	17.25	-0.06	17.57	-1.88
2	34.76	34.45	0.9	34.41	1.02



Conclusions

- The stochastic-based approach, FNNPSOGSA obtains superior results of damage quantification than that of the conventional ANN. Discrepancies in severity between target and estimation are -0.06% and 0.9% compared with -1.88% and 1.02% deriving from ANN.
- The proposed approach can generate a link between damage index and corresponding severity that can not observe if only damage index used.
- The accuracy and simple implementation of FNNPSOGSA confirm that it can serve as a potential assessment tool for real structures.

Further work: noise and experimental data should be used to verify the reliability and effectiveness of this approach.