INVESTIGATION ON THE ARTIFICIAL NEURAL NETWORKS PREDICTION CAPABILITIES APPLIED TO VIBRATING PLATES IN SIMILITUDE

A. Casaburo[1*], G. Petrone[1], V. Meruane[2], F. Franco[1], S. De Rosa[1]

[1]pasta-Lab
Department of Industrial Engineering, Aerospace section, Università degli Studi di Napoli Federico II, Via Claudio 21, 80125 Napoli, ITALY
Email: alessandro.casaburo@unina.it, giuseppe.petrone@unina.it, francof@unina.it, sergio.derosa@unina.it

[2]Department of Mechanical Engineering, Universidad de Chile, Beauchef 850, Santiago, CHILE
Email: vmeruane@uchile.it

ABSTRACT

The prediction capabilities of artificial neural networks in similitude field are investigated. They have been applied to plates in similitude with two objectives: prediction of natural frequencies and model identification. The results show that the method is able to give accurate predictions and that an experimental training set can be created if the models are well characterized.

1 INTRODUCTION

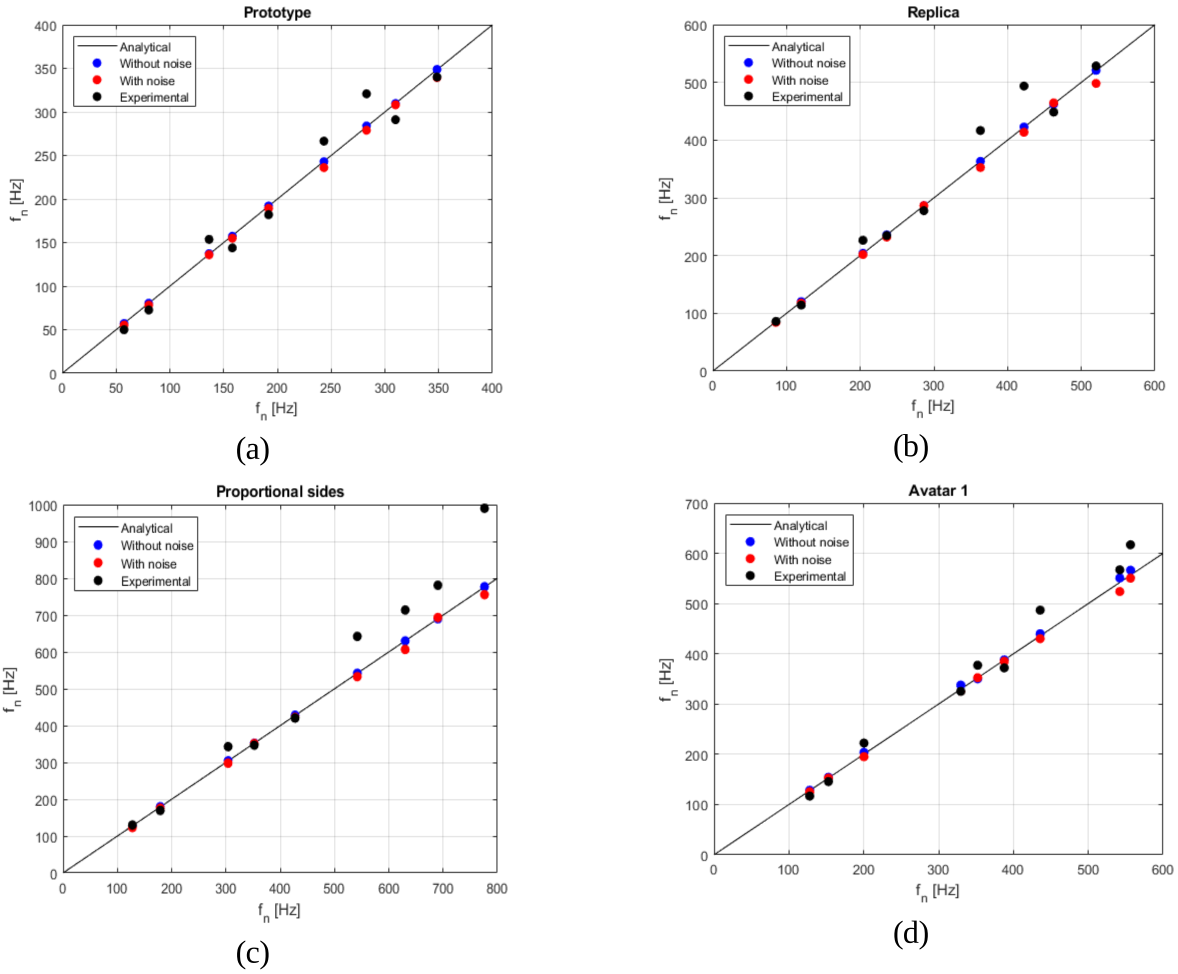
Similitude methods are valuable tools for experimental tests, allowing money and time saving, and simplifying the test setup by testing reduced scale models instead of full-scale prototypes. However, manufacturing limits or errors are the causes of distorted models production. For these models, there is no univocal law that allows the reconstruction of the prototype dynamic response [1]. ANNs (Artificial Neural Networks) [2] pattern recognition capabilities, already explored in [3], are thus investigated for two purposes: 1) prediction of the natural frequencies of clamped-free-clamped-free aluminium plates in similitude using a training set made, mainly, by distorted models; 2) model identification in terms of geometrical scale factors, using response parameters to characterize the models. For both the tasks, a sensitivity analysis has been executed in order to identify the best architecture and number of training examples returning an acceptable performance.

2 PREDICTION OF NATURAL FREQUENCIES

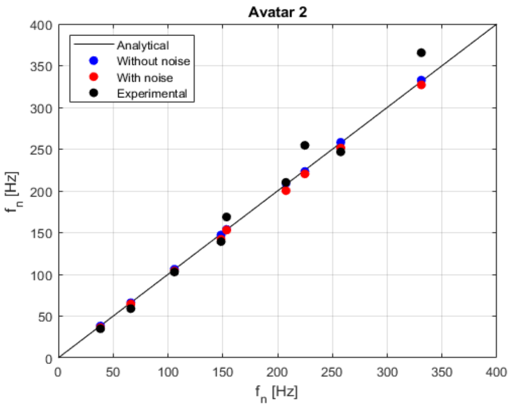
In the first task, the models are characterized in terms of geometrical scale factors (length, width, and thickness); the output to predict are the first nine natural frequencies. Two training sets are used: both analytical, one of them polluted with numerical random normally distributed noise, in an attempt to reproduce the experimental uncertainties.

Fig. 1 shows the predictions of the natural frequencies. Five panels, on which experimental tests were performed, are used to test the generalization capabilities of the ANN: the prototype, two complete similitudes and two distorted similitudes.

The blue dots are the predictions of the ANN trained on the analytical data, with architecture 20 – 15 – 10 and 4000 training examples. The red dots are the predictions of the ANN trained on polluted data, with architecture 10 – 10 and 6000 training examples. The predictions of the ANN are very close to the reference, the blue line. This is a proof of the efficiency and robustness to noise of ANNs. The results are validated by the experimental (black) dots, close to the values returned by the ANN. However, the number of training examples is prohibitive, and an experimental training set cannot be generated, at least with the model characterization herein used.



(a) (b) (c) (d)



(e)

Figure 1 - Comparison among the experimental natural frequencies and those predicted by the ANN in both the cases of polluted and not polluted training sets, for the prototype (a), replica (b), proportional sides (c), avatar 1 (d), avatar 2 (e).

3 MODEL IDENTIFICATION

In this task, model identification is performed. The aim is to distinguish replicas (all the geometrical dimensions scale in the same way), proportional sides (length and width scale in the same way) and avatars (all the geometrical dimensions scale differently).

The network architecture is 5 – 7 and uses 200 training samples. The dynamic response is used as input, characterized in terms of first and second natural frequencies, modal density and the first eigenvalue extracted by applying PCA (Principal Component Analysis) to the frequency response function of each model.

Table 1 lists the prediction of the scale factors of the five experimental panels. The prototype is perfectly identified. Length and width scale factors of the proportional sides are not quite the true ones, however the model can be still identified as proportional sides. Both the avatars are perfectly identified. The thickness scale factor of the replica, instead, deviates of 3% from the real scale factor. The error is not very high, but it prevents a complete model identification.

To have an idea of the error made on all the predictions, Fig. 2 shows the relative error map evaluated on 27,000 examples. In general, the errors are very low, around 1% – 2%. For each scale factor there is a region of higher error, in which peaks of 11% are reached. However, being maps of relative error, this is always in the range [-0.05, 0.05] for all the scale factors. Therefore, it is not very high, although it prevents an accurate model identification.

Table 1 – Predictions of the scale factors of the experimental plates.

	True (r_a, r_b, r_h)	**Predicted (r_a, r_b, r_h)**
Prototype	1.00, 1.00, 1.00	1.00, 1.00, 1.00
Replica	0.67, 0.67, 0.67	0.67, 0.67, 0.65
Proportional sides	0.67, 0.67, 1.00	0.66, 0.66, 1.00
Avatar 1	0.67, 1.00, 1.00	0.67, 1.00, 1.00
Avatar 2	0.99, 0.70, 0.67	0.99, 0.70, 0.67

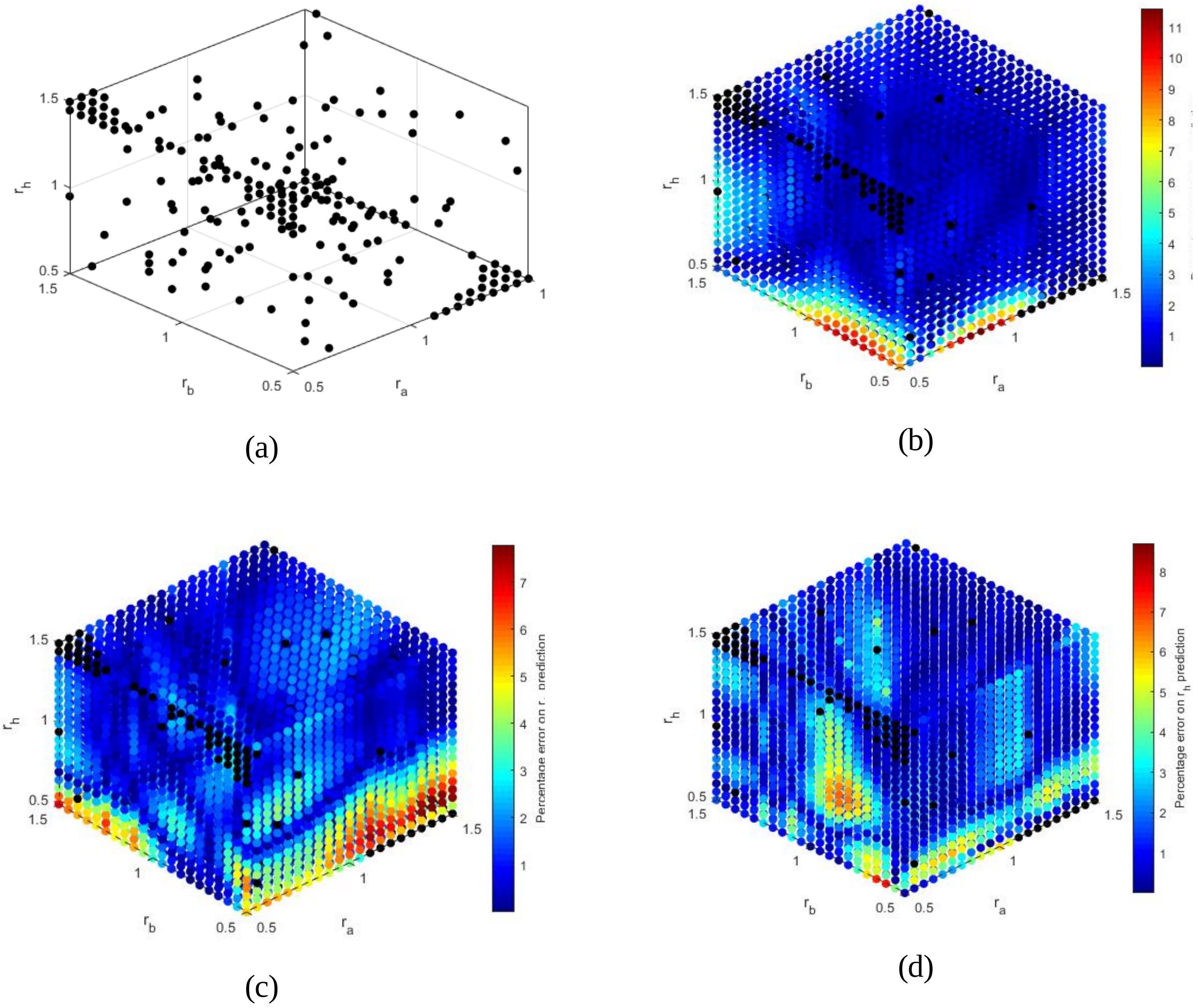


Figure 2 - Maps of the relative errors made by the ANN when predicting the scale factors. Subplot (a) shows the training examples, the other subplots the errors when predicting r_a (b), r_b (c), and r_h (d).

4 CONCLUDING REMARKS

The results demonstrated that ANNs have good potentialities in similitude fields, although too many samples are still required and the architecture cannot be defined *a priori*. However, the model identification task proved that, with a good characterization of input and output, it is possible to reduce significantly the number of training examples. ANNs proved to be also robust to noise. Using the method and analysing the results with critical thinking can make the application of ANNs an useful tool to support numerical simulations and experimental tests.

REFERENCES

[1] A. Casaburo, G. Petrone, F. Franco, and S. De Rosa. A review of similitude methods for structural engineering. *Applied Mechanics Reviews* 71(3), 2019.

[2] M. T. Hagan, H. B. Demuth, M. H. Beale and O. De Jesùs. Neural Network Design, 2nd Edition, Martin Hagan, USA, 2014.

[3] A. Casaburo, G. Petrone, V. Meruane, F. Franco and S. De Rosa, Prediction of the Dynamic Behavior of Beams in Similitude Using Machine Learning Methods. *Aerotecnica Missili e Spazio*, doi: https://doi.org/10.1007/s42496-019-00029-y, 2019.