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Artificial neural network surrogate modelling for random fields in structural stability

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Abstract

The growing importance of sustainable engineering solutions leads towards the design of slender and lightweight structures, which also entails a higher risk of stability problems. The buckling load of a structure is subject to noticeable uncertainties, which are strongly influenced by geometrical imperfections, see Figure 1. In a common stochastic approach, imperfections are simulated as random fields and applied to the finite element (FE) model as stress-free nodal displacements. The probability distribution of the buckling load can be determined via Monte Carlo Simulation. Considering polymorphic (mixed resp. hybrid) uncertainty in stability problems of complex structures, the computation time increases extremely, due to the double-loop of interval or fuzzy and stochastic analyses [1]. Furthermore, with the aim of a structural safety assessment, the calculation of a low probability of failure requires very time consuming simulations. In order to reduce the computation time, surrogate models are of crucial importance. Already developed approaches are, e.g., artificial neural network (ANN) based multilevel surrogate modelling [2], the polynomial chaos approach [3] and the control variates method [4]. The aim of the presented method is to use an ANN as surrogate model to predict the buckling load of a structure according to geometrical imperfections. The FE node values of the imperfections are the input data of the ANN, see Figure 2.

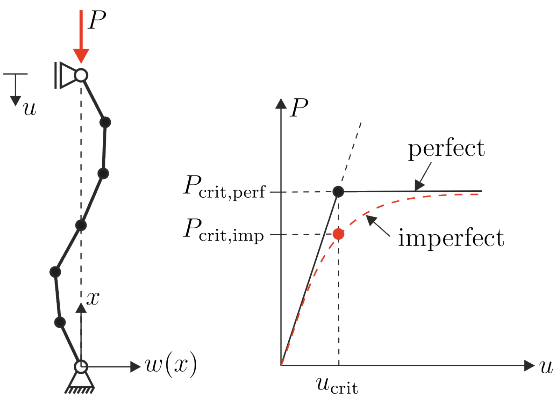

Figure 1: Buckling behavior of an imperfect structure compared to the perfect structure.

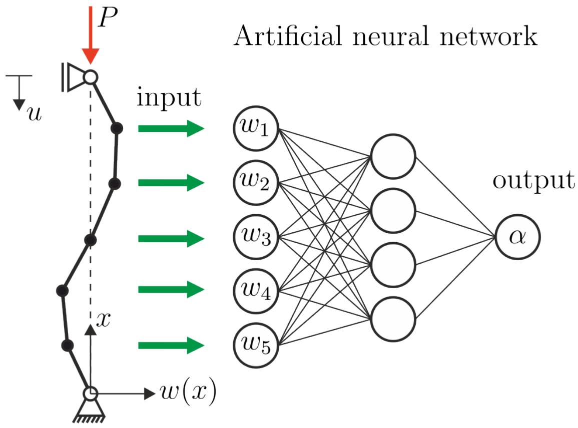

Figure 2: Artificial neural network to predict the critical load factor

The output of the ANN is the critical load factor α_{crit}, which is the ratio between the buckling load of the imperfect structure $P_{crit,imp}$ and of the perfect structure $P_{crit,perf}$: $\alpha_{crit} = P_{crit,imp}/P_{crit,perf}$. After successful training with random field realizations and the corresponding critical load factors computed by a geometrical nonlinear FE model, the network predicts the critical load factors αcrit of new random field samples and thus, is applied to perform the Monte Carlo Simulation.

The shape of the random field is determined by the correlation length Lc, which is very important in order to represent realistic imperfections. Often, the realistic imperfection shape is not known and thus, a range of correlation lengths Lc should be investigated. Therefore, the presented method is demonstrated for several correlation lengths in order to analyze the relationship between the correlation length and the training performance. A numerical example demonstrates that the presented ANN approach can effectively predict the probability distribution of the buckling load for structures with geometrical imperfections. A comparison of the FE and ANN solutions for two different correlation lengths is shown in Figure 3. Given the same amount of training information, the ANN performs better for higher correlations. To achieve the same quality for lower correlations, the ANN needs more training data. This shows, how the knowledge about the realistic correlation model is relevant for the training performance.

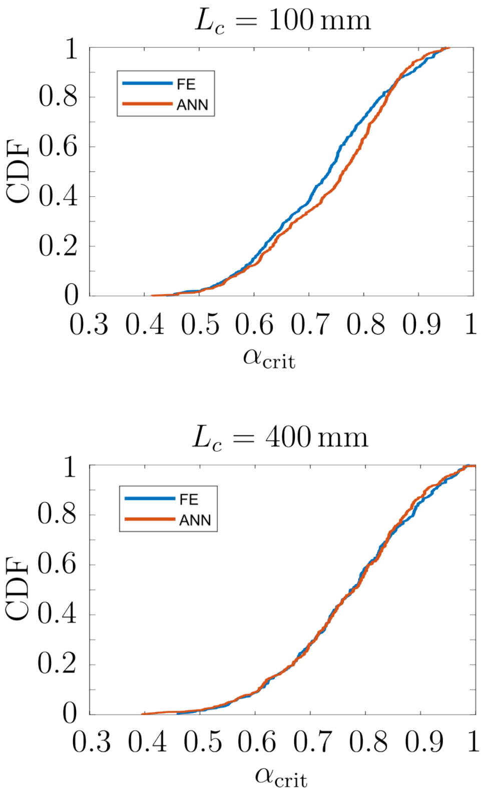

Figure 3: Comparison of the cumulative distribution functions (CDFs) of the critical load factor obtained by the FE and ANN solutions with a training set of 300 samples for two correlation lengths.

Keywords: Structural stability; artificial neural network; buckling behavior; geometrical imperfection; correlation length; correlated random field; surrogate modelling

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