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Review and application of Artificial Neural Networks models in reliability analysis of steel structures

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ABSTRACT

This paper presents a survey on the development and use of Artificial Neural Network (ANN) models in structural reliability analysis. The survey identifies the different types of ANNs, the methods of structural reliability assessment that are typically used, the techniques proposed for ANN training set improvement and also some applications of ANN approximations to structural design and optimization problems. ANN models are then used in the reliability analysis of a ship stiffened panel subjected to uniaxial compression loads induced by hull girder vertical bending moment, for which the collapse strength is obtained by means of nonlinear finite element analysis (FEA). The approaches adopted combine the use of adaptive ANN models to approximate directly the limit state function with Monte Carlo simulation (MCS), first order reliability methods (FORM) and MCS with importance sampling (IS), for reliability assessment. A comprehensive comparison of the predictions of the different reliability methods with ANN based LSFs and classical LSF evaluation linked to the FEA is provided.

1. Introduction

The methods for structural safety assessment aim at evaluating the probability of limit state violation by comparing the probabilistic models of acting loads and resistance of a structural component or system. A limit state is a condition beyond which a structure exceeds a specified design requirement expressed in a mathematical form by a limit state function $g(\mathrm{X})$. The failure probability (P_f) is then defined as the probability of occurrence of the failure event $g(\mathrm{X}) \leq 0$, where X is a vector of random variables that represents the uncertainties on the loads and on the material and geometrical properties of the structure.

Available methods for reliability assessment can be categorized into two main groups: gradient-based and simulation-based methods [1]. The first group consists in an iterative minimization procedure based on the limit state function gradient estimation in order to find the design point, which is a point on the failure surface with the highest probability density, also denoted as the most likely failure point. The traditional first-order reliability method (FORM) [2–4] and the second-order reliability method (SORM) [5–8] belong to this class.

The simulation techniques have their origin in Monte Carlo simulation (MCS) method, which generates a large sample set of limit state evaluations and approximates the true value of the probability of failure by identifying the number of samples falling into the failure domain. Despite its simplicity, this method may become not feasible if the deterministic structural analysis is time-consuming and especially for problems involving low probability of failure, which are the usual ones in structural reliability. In order to further improve the computational efficiency of MCS, many variance reduction techniques have been proposed [9], including importance sampling [10,11], directional simulation [12] or subset simulation [13,14]. Despite these improvements, the MCS method is still time-consuming and further development is crucial. The above described methods are less suitable for the reliability analysis of complex structures with $g(\mathrm{x})$ defined implicitly, i.e., the evaluation of $g(\mathrm{x})$ requires a time-consuming numerical calculation of the structural response by mean of finite element analysis (FEA). In gradient-based approaches such as FORM, the performance function is approximated by a linear function in a normalized space at the design point and poor accuracy can result from strongly nonlinear performance functions. Moreover, when the LSF has an implicit form, the computational cost of the calculations can be very high. In the simulation methods the problem rests in the enormous number of simulations

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required for the reliability estimations, since the allowable P_f of structures is usually very low.

To overcome these problems, various methods for LSF approximation have been proposed. Among the techniques available to cope with implicit limit state functions, the response surface method (RSM) has proved to be an efficient and widely applicable method in structural reliability analysis. In this method, typically first- or second-order polynomials are chosen to replace the real limit state function [15–18].

Kmiecik and Guedes Soares [19] have used the RSM for probabilistic modeling of the strength of compressed steel plates and, recently, Teixeira and Guedes Soares [20] extended the use of this technique to reliability problems involving random fields of corrosion, although random fields of initial distortions could also be considered [21]. Gaspar et al. [22] have combined a response surface approach with a Monte Carlo based simulation method to efficiently solve structural system reliability problems that involve nonlinear finite element analysis.

Artificial Neural Network (ANN) algorithms introduced as universal function approximations [23] have also been used for structural reliability assessment by several researchers, (e.g., [23–27]). ANNs are mathematical models based on the neural structure of the brain. ANNs have the ability of establishing a functional relationship between two data spaces during a learning process and reproduce that connection during a recall process. Various kinds of ANN can be distinguished and many studies on its efficiency and accuracy have been published. The most popular ANN architecture also applied in this study is the multi-layer feed forward network.

Cardoso et al. [28] have shown that ANN is a versatile methodology that can approximate accurately highly non-linear functions over the entire domain with very good precision. Several studies have also been performed showing the accuracy and efficiency of the ANN-based response surface method for reliability assessment in comparison with the conventional response surface methods. Gomes and Awruch [27] indicated that the ANN approach is more efficient, however, the examples considered were relatively simple. More recently, Bucher and Most [25] have applied these approximation methods to several examples of nonlinear structural analysis concluding that the relative accuracy of the various approaches depends on the specific problem under consideration.

The present paper reviews the development and use of ANN models in structural reliability analysis covering the different types of ANNs, the methods of structural reliability assessment that are typically used, the techniques proposed for ANN training set improvement and also some applications of ANN approximations to structural design and optimization problems.

In the second part of this paper, Artificial Neural Network models are applied in the reliability analysis of a ship stiffened panel subjected to uniaxial compression loads induced by hull girder vertical bending moment, for which the collapse strength is obtained by means of nonlinear finite element analysis (FEA). In this application ANN models are used for LSF approximation and combined with Monte Carlo simulation (MCS), first order reliability methods (FORM) and Monte Carlo simulation with importance sampling (MCIS) techniques for reliability assessment. In particular, an adaptive ANN-based MCIS approach using ANN-based FORM for search of the design point is proposed and its efficiency compared with MCIS with LSF evaluation based on direct FEA.

2. ANN models for limit state function approximation

In the ANN, the neuron is a processing element with several inputs and one output [23]. Each neuron m receives an input signal vector $X = x_1, x_2, \ldots, x_n$ from n input channels. Next, the weighted sum of x is calculated by multiplying each element x_k by a coefficient w_{mk} demonstrating adequate importance of the input channel k. The m-neuron activation a_m is given by:

$$a_m = \sum_{k=1}^{n} w_{mk} \cdot x_k + b_m \tag{1}$$

where b_m called bias, is a constant corrective term which allows having a non-negative activation a_m, when all elements of the input vector X are equal 0. The output signal value s_m is calculated as a function of the activation, called the transfer function $f(a_m)$. Sigmoid transfer functions are typically used for this purpose and a common choice is the hyperbolic tangent sigmoid transfer function:

$$f(a_m) = \frac{2}{1 + e^{-2a_m}} - 1 \tag{2}$$

The architecture of a single neuron is shown in Fig. 1.

The multi-layer feed forward network consists of various neurons situated on three or more layers – input layer, output layer and one or more hidden layers in between them. The number of neurons on the input layer is equal to the number of input variables while on the output layer it depends on the number of functions to approximate. However, selection of networks optimal architecture is not a simple task and no general rules are applicable for the number of hidden layers and number of the neurons on the hidden layer estimations. In general, the higher the complexity of a problem, the larger the number of processing elements in hidden layer is needed for a good approximation level and often this is found based on a trial-and-error process. Fig. 2 shows the architecture of an example network with 3, 4 and 2 neurons, respectively on input, hidden and output layer.

The training of a network is an iterative process and consists in obtaining the unknown weights w_{mk} and biases b_m required for the LSF approximation. The initial weights and biases are set to random values and are subsequently updated by the training algorithm. For this purpose, the training data set with input and target values must be previously prepared. The set is then divided into two sub-sets: (1) the training sub-set which is used for updating the weights and biases and (2) the validation sub-set, used for stopping the training when the network performance fails to improve for previously specified number of iterations or for checking the network approximating capacities. The iterative training algorithm performs an error minimization procedure that is repeated until the network outputs converge to the target values.

The selection of a representative group of samples for training purposes is an important task. To improve training efficiency, each variable should be covered with a sufficient number of samples so that in the recall process the network can approximate the LSF successfully in its entire domain. The size of the sample set grows

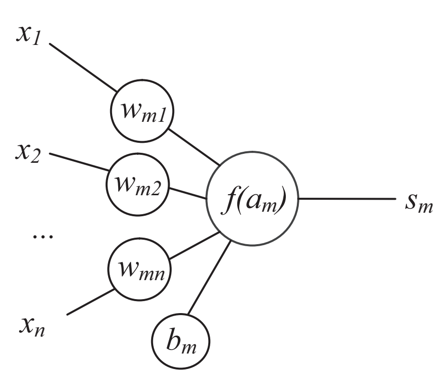

Fig. 1. Artificial neuron.