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An artificial neural network based genetic algorithm for estimating the reliability of long span suspension bridges

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ABSTRACT

An accurate and efficient artificial neural network (ANN) based genetic algorithm (GA) is presented for estimating the reliability of long span suspension bridges. In this method, the training datasets for establishing an ANN model are generated by uniform design method and are distributed uniformly over the entire design space. The explicit formulation of the approximate limit state function is then derived by using the parameters of the developed ANN model. Once the explicit limit state function is obtained, the failure probability can be easily estimated by using an improved GA that introduces new approach for the penalty function and coded method and GA operators. A numerical example involving a detailed computational model of a long span suspension bridge with a main span of 1108 m is presented to demonstrate the applicability and merits of the present method. Finally, several important parameters in the present method are discussed.

1. Introduction

The first efforts to apply the GA method to structural reliability analysis were published more than 10 years ago [1,2]. Although the GA method has seen great success in the context of reliability analysis, it encounters efficiency-related difficulties in dealing with a complex problem. To defeat this problem, many researchers [3,4] have adopted the Shredding Genetic Algorithm (SGA) to predict the reliability index. The SGA is more economical than the traditional GA method, and yet the results obtained have been reasonably accurate. Nevertheless, the SGA requires that the user has to be acquainted with genetic algorithms in-depth, and is not likely to become widely used in practical applications. Also, the reliability analysis of structures with large number of degrees of freedom using the SGA will have the huge computational volume and will be very time consuming [5].

Artificial neural network (ANN) based GA [5,6] has been recently developed as an efficient GA method for the reliability analysis of structures. Its efficiency stems from the introduction of an explicit approximate limit state function. The explicit formulation of the approximate limit state function is derived by using the parameters of the ANN model. By introducing the derived approximate limit state function, the failure probability can be easily calculated using traditional GA method, practically when the limit state functions are not explicitly known. On the other hand, for reliability analysis of complicated structures, the ANN based GA method becomes very efficient after the explicit limit state function is found, without having to perform time-consuming deterministic finite element analyzes. Moreover, the ANN based GA method can directly take advantage of existing finite element software without modification, and thus is convenient to be used for practitioner engineers.

Until now, there are two ANN based GA methods: traditional ANN based GA (ANN-GA) [5] and systematic ANN based GA (SYS-ANN-GA) [6]. The important difference between the two methods is that the SYS-ANN-GA uses the uniform design method instead of the random method in the traditional ANN-GA for selecting the training datasets for establishing an ANN model. As indicated in Cheng and Li [6], the SYS-ANN-GA method proves to be effective and could be more efficient than the traditional ANN-GA method when dealing with problems where closed-form failure probability functions are not available or the estimated failure probability is extremely small. In the SYS-ANN-GA method, however, the used genetic algorithms were found to be too simple and thus reduced the capacity of GA to identify local optima in routine reliability analyzes. Therefore, there are certain rooms for further improvement of its efficiency and capability, which is a very important issue when the method is applied to a complex structure.

Regarding the issue of applicability of the aforementioned ANN-based GA approach for reliability analysis of a long span suspension bridge, to the authors' knowledge, no result is reported in the published literature. The present paper is regarded as a contribution on this research topic.

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The emphasis of the work to be presented in this paper has therefore been to explore and develop a new ANN-based GA method that has the capability to offer robust and accurate estimates of failure probability of long span suspension bridges. For this purpose, the formulation of a structural reliability problem is first presented in Section 2. The ANN based GA method developed previously for the structural reliability problem is reviewed in Section 3. Section 4 proposes a new ANN based GA method for structural reliability analysis by using an improved GA that introduces new approach for the penalty function and coded method and GA operators. In Section 5, a numerical example involving a detailed computational model of a long span suspension bridge with a main span of 1108 m is presented to demonstrate the applicability and merits of the proposed method. Section 6 discusses several important parameters in the proposed method. Finally, some conclusions are drawn in Section 7.

2. Structural reliability problem

Before proceeding to the development of the new ANN based GA, it is necessary to present the formulation of a structural reliability problem for the sake of future reference.

A reliability problem can be formulated in the following form

$$\text{Minimize}\beta = \|\mu\|^2 = \mu^T \cdot \mu \,\text{Subject to} : g(\mu) = 0 \tag{1}$$

where μ, vector of standard normal variants; β, reliability index; $g(\mu)$, limit state function. In the present study the reliability of long span suspension bridges is investigated. Thus the limit state function in Eq. (1) is not available as an explicit, closed-form function of the input variables. In other words, the limit state function is implicit.

3. Review of ANN based GA methods

As described in the previous sections, two ANN based GA methods could be pursued for the reliability analysis of structures with the above-mentioned implicit limit state function: traditional ANN-GA and SYS-ANN-GA. Considering that the SYS-ANN-GA always outperforms the traditional ANN-GA [6], only the SYS-ANN-GA is reviewed in this section. The SYS-ANN-GA method is based on three key concepts: (1) the selection of training datasets for establishing an ANN model by the UDM; (2) approximation of the limit state function by the trained ANN model; and (3) estimation of the failure probability using the simple GA. The details of these concepts are described in the following sections.

3.1. Selection of training datasets

The selection of training datasets is an important issue in the context of establishment of the ANN model. The main aim in the selection of training datasets is to make the selected training data as uniformly distributed as possible to cover the entire design space. In the SYS-ANN-GA, all training data are selected using the UDM. It has been reported in the literature [6] that the use of the uniform design method may improve the quality of the selected training datasets, leading to a better performance of the ANN model. Some of its essential features in the context of establishment of the ANN model are discussed very briefly in the following sections.

3.1.1. Introduction of the UDM

The UDM was initially developed for seeking experimental points to be uniformly scattered in a domain. A distinctive feature of the method is the introduction of number-theoretic method [7]. The essence of the number-theoretic method is to find a set of points that is uniformly scattered over a s-dimensional unit cube and this set is used instead of random number in Monte Carlo method (i.e., quasi random numbers). The UDM has the following advantages [8]: (1) it is able to produce samples with high representativeness in the domain; (2) it imposes no strong assumption on the model; and (3) it accommodates the largest possible number of levels for each factor among all experimental designs. Due to these advantages, the UDM has been applied to the fields of chemistry and chemical engineering, pharmaceutics, quality engineering, system engineering, survey design, computer sciences and natural sciences. However, the application of the UDM to reliability analysis of structures is quite limited. An attempt was made to apply the UDM to the reliability analysis of structures in the context of traditional ANN-GA [6]. The findings of this work clearly indicate the potential of the UDM, which generally selects training datasets more uniformly distributed in the given domain than the traditional ANN-GA, leading to a better performance of the trained ANN model.

3.1.2. Implementation of the UDM

In the SYS-ANN-GA, the most important part of using the UDM is to choose suitable training datasets. This is achieved in this paper as follows:

(1) Some basic parameters such as the range of the domain, the number of experiments (training data) and the number of levels of each factor (random variable) are defined.
(2) The range of the domain is uniformly divided by the number of levels of each factor, and then the factor levels are coded to some values such as 1, 2, 3, and etc.
(3) The defined parameters and coded values are used to choose a uniform design table so that the desired training data can be easily obtained. For convenient use of the UDM, many tables of the UDM are available. A table of the UDM is denoted by U_n (q^t), where "U" represents the UDM, "n" the number of experiments, "q" the number of levels of each factor, and "t" the maximum number of columns of the table. Table 1 shows a table of the UDM, U_{37} (37^{12}). Note that different choices among the columns result in experimental points (selected training data) with different discrepancies. Therefore, a recommendation of columns with minimum discrepancy for a given number of factors is needed. For this purpose, a corresponding accessory table is provided for each table of the UDM. For example, Table 2 is the accessory table of Table 1. If two factors are involved in the experiments, according to Table 2, the choice of columns 1 and 7 results in a set of experimental points (selected training data) with the minimum discrepancy. Although the details of tables of the UDM cannot be given here due to lack of space, they can be found in Refs. [7,9].

In this way, the SYS-ANN-GA method can select more representative training datasets than the traditional ANN-GA method, as discussed in detail in Cheng and Li [6].

The key step of the SYS-ANN-GA method is the choice of a proper uniform design table. While the aforementioned uniform design tables can guarantee that the generated data cover the entire design space uniformly, the maximum number of training data generated by the uniform design table is limited to 37. However, in complicated problems where the number of random