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Dynamic neural network method-based improved PSO and BR algorithms for transient probabilistic analysis of flexible mechanism

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ABSTRACT

To improve the computing efficiency and precision of transient probabilistic analysis of flexible mechanism, dynamic neural network method (DNNM)-based improved particle swarm optimization (PSO)/Bayesian regularization (BR) (called as PSO/BR-DNNM) is proposed based on the developed DNNM with the integration of extremum response surface method (ERSM) and artificial neural network (ANN). The mathematical model of DNNM is established based on ANN on the foundation of investigating ERSM. Aiming at the high nonlinearity and strong coupling characteristics of limit state function of flexible mechanism, accurate weights and thresholds of PSO/BR-DNNM function are discussed by searching initial weights and thresholds based on the improved PSO and training final weights and thresholds by the BR-based training performance function. The probabilistic analysis of two-link flexible robot manipulator (TFRM) was investigated with the proposed method. Reliability degree, distribution characteristics and major factors (section sizes of link-2) of TFRM are obtained, which provides a useful reference for a more effective TFRM design. Through the comparison of three methods (Monte Carlo method, DNNM, PSO/BR-DNNM), it is demonstrated that PSO/BR-DNNM reshapes the probability of flexible mechanism probabilistic analysis and improves the computing efficiency while keeping acceptable computational precision. Moreover, the proposed method offers a useful insight for reliability-based design optimization of flexible mechanism and thereby also enriches the theory and method of mechanical reliability design.

1. Introduction

Flexible mechanism is defined as the mechanism system comprising a plurality of flexible components, which is an indispensable part in mechanical system, such as spacecraft, satellite and so forth [1–3]. The coupling effect between motion and deformation of flexible components cause the high nonlinearity and dynamics of kinematic parameters and kinetic parameters, which leads to the difficulty of design analysis of flexible mechanism [4,5]. Therefore, efficient analysis methods are expected to reasonably design flexible mechanism. Although much progress of experimental and numerical investigations has been implemented for flexible mechanism via deterministic analysis methods [6–8], these works are not always concerned the uncertainty and randomness of various factors impacting on the performance of flexible mechanism. Probabilistic analysis is one viable alternative, which concerns stochastic factors just like geometry sizes and material parameters, and describes the responses of flexible mechanism with acceptable precision as well [9–12]. The probabilistic analysis has been widely applied in many fields [13–15]. Nevertheless, probabilistic design method is one key technique for the probabilistic analysis of flexible mechanism.

Classic probabilistic analysis methods are Monte Carlo method (MCM) [16,17], response surface method (RSM, also called surrogate model) [18,19] and extremum response surface method (ERSM) [20,21]. MCM applied in many fields holds high computing precision in the reliability evaluation and design. However, it is very difficult for MCM to cater for the requirements of solving multiple dynamic equations with characteristics of nonlinearity, time variation and strong coupling. RSM, as one focus of structural probabilistic analysis is promising to improve computing efficiency and precision [18]. Nevertheless, RSM hardly perform nonlinear transient probabilistic analysis of flexible mechanism because RSM requires calculating all of responses and holds unacceptable computing precision. To processing the nonlinearity and dynamic problem in the reliability analysis of flexible mechanism, ERSM was

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developed by the focus on the extremum responses of flexible mechanism [20]. However, it is not perfect to describe the nonlinearity and dynamic characters in probabilistic analysis due to its extremum response surface function (ERSF) fitted by quadratic polynomial with insufficient accuracy and efficiency [21–23]. Therefore, it is anticipant to develop a more efficient approach to improve efficiency and precision for nonlinear transient probabilistic analysis of flexible mechanism by improving ERSM.

To enhance the approximate performance and computing power of ERSM, one viable program is to establish ERSF based on feasible surrogate model with higher fitting accuracy. Artificial neural network (ANN) model, which is regarded as an intelligent learning method with the advantages of strong nonlinear mapping ability and good robustness ability, is widely applied to data mining [24,25] and reliability prediction [26,27]. Along those advantages of ANN, ERSM based on ANN, which is called as dynamic neural network method (DNNM), is proposed for transient probabilistic analysis. DNNM integrates the strong nonlinear mapping ability of ANN and simplified calculation ability of ERSM. However, the overfitting and local optimization problems in DNNM training process always occur while time-varying and high nonlinear limit state function is fitted so that the prediction accuracy of DNNM is influenced and its further application in transient probabilistic analysis of flexible mechanism suffers from restriction.

The purpose of this study is to develop an efficient surrogate method (PSO/BR-DNNM) to improve the computational efficiency and precision of the transient probabilistic analysis of flexible mechanism, by adopting the improved PSO algorithm to search the initial weights and thresholds of ANN and the proposed BR algorithm -based training performance function to train the final weights and thresholds. The proposed PSO/BR-DNNM is verified by the transient probabilistic analysis of two-link flexible robot manipulator.

In what follows, Section 2 discusses the basic theory of PSO/BR-DNNM based on ERSM, ANN and DNNM for transient probabilistic analysis, and gives the strengths of PSO/BR-DNNM. Section 3 investigates the thought of the transient probabilistic analysis of flexible mechanism with PSO/BR-DNNM. The proposed method is validated by TFRM probabilistic analysis in Section 4. Section 5 summaries some conclusions on this study.

2. Basic theory

2.1. DNNM

2.1.1. Basic thought of ERSM

ESRM is an important surrogate model in transient probabilistic analysis, which calculates only the extreme values of output response rather than all values of dynamic output response under different input vectors within a time domain. ERSM transforms a stochastic process of output responses into the random variables. Obviously, ERSM is a heuristic way to save computing time and enhance calculation efficiency in the transient probabilistic analysis of flexible mechanism [21]. The basic principle of ERSM is shown in Fig. 1.

Assuming that the output response of jth input vector $\boldsymbol{x}_j$ is $\boldsymbol{Y}_j(t, \boldsymbol{x}_j)$, the dynamic extremum of $\boldsymbol{Y}_j(t, \boldsymbol{x}_j)$ within the time domain [0, T] is $\boldsymbol{Y}_{j,\max}(\boldsymbol{x}_j)$. The data set $\{\boldsymbol{Y}_{j,\max}(\boldsymbol{x}_j): j = 1, 2, \ldots, l\}$ consisting of the maximum output responses are used to fit the extremum response surface function ERSF $f(\boldsymbol{x})$, and the extremum response curve $Y(\boldsymbol{x})$ can be expressed by

$$Y(\boldsymbol{x}) = f(\boldsymbol{x}) = \{Y_{j,\max}(\boldsymbol{x}_j) : j = 1, 2, \ldots, l\} \tag{1}$$

ERSF is a key factor for transient probabilistic analysis since a valid ERSF is beneficial to enhance efficiency and precision. As to the transient probabilistic analysis of flexible mechanism, it is difficult to fit ERSF with a high precision and acceptable efficiency, because of the dynamic equations of flexible mechanism has the characteristics of high nonlinearity and strong coupling. To address this issue, the fitting model with high computing precision and efficiency should be developed.

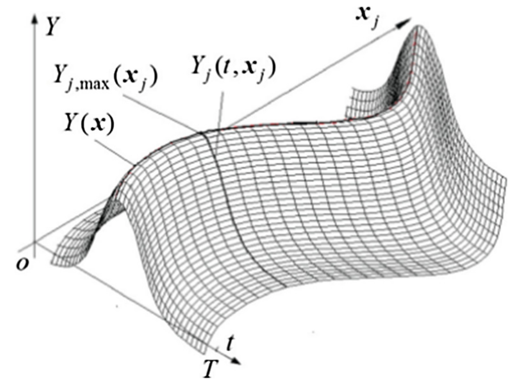

Fig. 1. Basic thought of ERSM.

2.1.2. Property of ANN model

Back propagation-artificial neural network (BP-ANN) algorithm is able to effectively fit the complex nonlinear functional relationship between input vector $\boldsymbol{x}_j = [x_1, x_2, \ldots, x_l]$ $(j = 1, 2, \ldots, n)$ and output response $\boldsymbol{y}_{j,\max}(\boldsymbol{x}_j)$, because of the characteristics of arbitrary shape and strong self-adaptation may reduce the number of required samples and reasonably deal with the nonlinearity. Therefore, BP-ANN model to construct ERSF can obtain the output responses without solving a large amount of dynamic equations, which greatly reduces the amount of computation and increases the computational speed. BP-ANN topology model is shown in Fig. 2, in which j is the jth sample, n is the number of samples and $\boldsymbol{l}$ is the number of input variables.

The neuron number of input layer n_i and output layer n_o are determined by the number of input vector and output response, respectively. The neuron number of hidden layer n_h can be obtained by

$$n_h = \sqrt{n_i + n_o} + r \tag{2}$$

where r indicates the empirical number during domain [0,5].

2.1.3. ERSM based on ANN, DNNM

For the time-varying and nonlinear characteristics of flexible mechanism probabilistic analysis, BP-ANN model is chosen to fit the ERSF of limit state equation, called as dynamic neural network

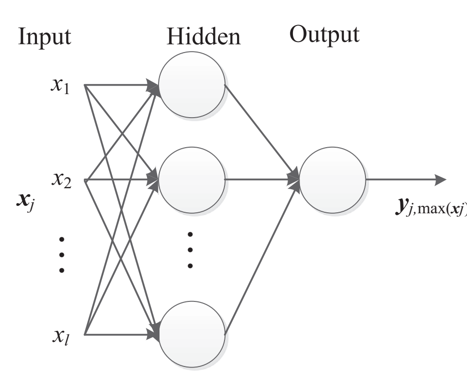

Fig. 2. BP-ANN topology model.