

An Improved Prediction Algorithm for Noise of Transformer Considering Material Parameter Uncertainty

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This study develops a computationally efficient framework for probabilistic transformer noise prediction under material uncertainties. To accurately characterize the uncertainty in silicon steel material parameters, the magnetization and magnetostriction laws are stochastically modeled using vine copula theory, generating correlated parameter sets. Then, to address computational challenges in uncertainty propagation analysis, an adaptive differential evolution algorithm-optimized backpropagation neural network (ADE-BPNN) is proposed. The proposed method is finally applied to the magneto-structural-acoustic coupling model of a transformer to validate its effectiveness and accuracy. Numerical results indicate a 12.7% probability of noise exceeding design thresholds due to magnetic parameter variations, highlighting critical considerations for low-noise transformer optimization.

Index Terms— magnetic material, noise level, backpropagation algorithms, stochastic theory

I. INTRODUCTION

THE magnetization and magnetostriction properties of silicon steel sheets are critical coupling parameters between the electromagnetic and structural fields of transformers [1], with uncertainties caused by microscopic non-uniformity and manufacturing tolerances [2]. However, traditional deterministic modeling typically averages out fluctuations in material parameters and manufacturing errors, making it difficult to accurately capture their impact on transformer performance uncertainty.

To overcome these difficulties, this work proposes two methods: - a stochastic modeling method for magnetization and magnetostriction curves based on vine copula theory, - a method employing an adaptive differential evolution algorithm-optimized BPNN (ADE-BPNN) for probabilistic noise prediction.

The simulation results demonstrate that the copula theory-based joint probability density of material parameters incorporates both their probability distribution and correlations, generating sample curves that better reflect real-world conditions. The developed algorithm significantly reduces computational costs while improving prediction accuracy and processing speed. This study provides methodological support for selecting silicon steel core materials and facilitates structural optimization in transformer design.

II. METHODOLOGY

A. Stochastic modeling method based on copula theory

Taking a three-dimensional random vector $\mathbf{X} = \{x_1, x_2, x_3\}$ with marginal probability density functions $f_i(x_i)$ as an example. The corresponding vine tree structure is shown in Fig.1.

Based on vine copula theory, the joint probability density of $\mathbf{X}$ can be expressed as follows [3]

$$f(x_1, x_2, x_3) = c_{23|1}(F_{2|1}(x_2 | x_1), F_{3|1}(x_3 | x_1)) \cdot c_{12}(F_1(x_1), F_2(x_2)) \cdot c_{13}(F_1(x_1), F_3(x_3)) \cdot f_1(x_1) \cdot f_2(x_2) \cdot f_3(x_3) \quad (1)$$

where, $f_i(\cdot)$ and $F_i(\cdot)$ represent the probability density distribution and cumulative distribution of x_i , respectively; $c(\cdot)$ denotes the unique copula density function of the random vector; $F(\cdot|\cdot)$ represents the conditional probability distribution function. By calculating the marginal probability density of the random variable and the copula function that describes the correlation structure between variable pairs, the multivariate joint probability distribution model can be constructed. Subsequently, correlated parameter samples can be generated using a conditional sampling algorithm.

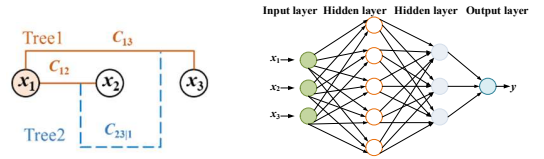


Fig. 1. Schematic diagram of vine tree. Fig. 2. BP neural network structure.

B. Adaptive DE algorithm optimized BP neural network

(1) Adaptive DE algorithm

The DE algorithm is a robust population-based global optimization approach, consisting of initialization, mutation, crossover, selection, and boundary handling. The key step is to create a mutation vector $\mathbf{V}_{j,G}$ for each target vector $\mathbf{X}_{j,G}$ from the current population. To address the high sensitivity of control parameters and the limited local neighborhood search capability of the DE algorithm, this paper improves the mutation mechanism by integrating the traditional DE algorithm's mutation operator with the Jaya algorithm [4]. The improved mutation mechanism is as follows:

$$\mathbf{v}_j = \begin{cases} \mathbf{x}_{i,r'_1} + F(\mathbf{x}_{i,r'_2} - \mathbf{x}_{i,r'_3}) & \text{rand}[0,1] > 0.3 \\ \mathbf{x}_{i,j} + \text{rand}_{1,i} \times (\mathbf{x}_i^{\text{best}} - |\mathbf{x}_{i,j}|) & \text{otherwise} \\ -\text{rand}_{2,i} \times (\mathbf{x}_i^{\text{worst}} - |\mathbf{x}_{i,j}|) & \end{cases} \quad (2)$$

where, $\text{rand}_{1,i}$ and $\text{rand}_{2,i}$ are random values following a uniform probability distribution in the range $[0,1]$, and $|\mathbf{x}_{i,j}|$ represents the absolute value of solution $\mathbf{x}_{i,j}$. And $\text{rand}_{1,i} \times (\mathbf{x}_i^{\text{best}} - |\mathbf{x}_{i,j}|)$ guides the new solution toward the optimal solution, while $\text{rand}_{2,i} \times (\mathbf{x}_i^{\text{worst}} - |\mathbf{x}_{i,j}|)$ drives it away from the worst solution.

When the random value is less than or equal to 0.3, the Jaya mutation operator is chosen; otherwise, the DE mutation operator is applied. Thus, for each generation vector, the two mutation operators are randomly selected with a ratio of 0.7:0.3.

(2) ADE-BPNN

The standard BPNN algorithm initializes network weights and thresholds randomly, then iteratively adjusts parameters via gradient descent using training samples. The training phase concludes when the output mean square error attains the predefined threshold, thereby establishing the final network configuration [5]. The network structure is illustrated in Fig.2. However, the algorithm's reliance on initial parameters often traps it in local minima, compromising prediction accuracy. To overcome this limitation, this study integrates ADE with BPNN. The ADE algorithm first performs a global search for optimal parameters, which then initialize the BPNN. As shown in Fig.3, each ADE solution encodes a complete parameter initialization configuration for the BPNN.

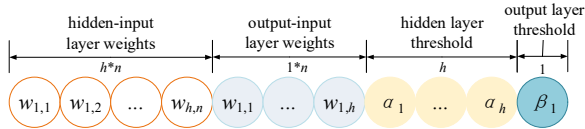


Fig. 3. Structure of an individual.

C. Overall framework for quantifying uncertainty

This methodology integrates five critical components:

Step 1: Constructing joint probability distributions for the magnetostriction and magnetization model parameters.

Step 2: Generating correlated material parameter sets through conditional sampling from the joint distributions.

Step 3: Implementing an ADE algorithm to identify globally optimal initial weights and thresholds for the BPNN.

Step 4: Developing the neural network model through training on 180 material parameter-noise response pairs for accurate noise prediction.

Step 5: Predicting 10 000 noise realizations through the calibrated model for comprehensive statistical characterization.

III. APPLICATION AND RESULTS

The deterministic models for the magnetization and magnetostriction properties involve six parameters to be determined, as specified in (3) and (4).

$$H = a_1 B + a_2 B^{a_3} \quad (3)$$

$$\lambda = \lambda_s \left(\frac{M_{an}^2}{M_s^2} - \chi \frac{M_{an}^4 - M_s^4}{M_s^4} \right) \quad (4)$$

where, H denotes the magnetic field intensity, B represents the magnetic flux density, a_1 , a_2 , and a_3 are constants; λ stands for magnetostriction, M_{an} is anhysteretic magnetization, M_s denotes saturation magnetization, λ_s is the saturation magnetostriction coefficient, and χ is a constant coefficient.

The conditional sampling algorithm generates 200 parameter sets that comprehensively cover the experimental data while preserving accurate parameter correlations, as illustrated in Fig. 4. These samples are then used as inputs for the transformer

finite element model to generate corresponding sound pressure level responses for uncertainty analysis.

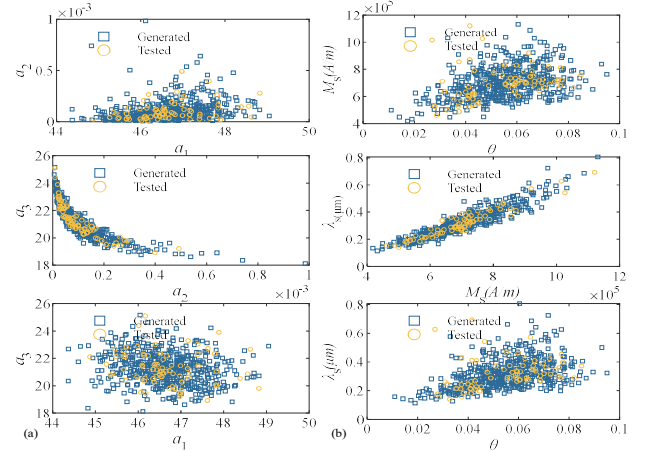


Fig. 4. (a) Scatter plots of 200 parameter pairs simulated from Frank-Gaussian-Gaussian (b) Scatter plots 200 parameter pairs simulated from Clayton-Gaussian-Gaussian

Fig.5 and Table I compare the performance metrics across different approaches. The unoptimized BP neural network requires 2.43 seconds for training, while the ADE-optimized versions complete training in 1.75 seconds. Three standard statistical metrics confirm the superior prediction accuracy of ADE-BPNN. Using the trained model to generate 10 000 noise realizations reveals a 12.7% probability of exceeding the 45 dB threshold due to variations in material parameters.

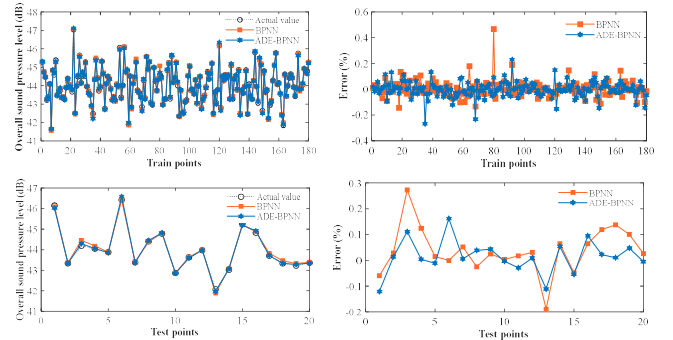


Fig. 5. Comparison of prediction results of BPNN and ADE-BPNN algorithms

TABLE I
PREDICTION ERRORS OF BPNN AND ADE-BPNN

Algorithm	Time	ERROR	RMSE	MAPE
BPNN	2.43 s	0.14 %	0.076	0.139 %
ADE-BPNN	1.75 s	0.07 %	0.041	0.067 %

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