A Novel Crosstalk Estimation Method for Twist Non-Uniformity in Twisted-Wire Pairs

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ABSTRACT Based on the research of Monte Carlo (MC) method and adaptive beetle antennae search (ABAS) algorithm, a new crosstalk estimation method for non-uniform pitch twisted pair is proposed in this paper. First, the model of non-uniform pitch twisted pair is established based on the principle of twisted pair production. Then, the MC method and ABAS-BPNN (back propagation neural network) algorithm are used to construct a parasitic parameter mean extraction network for non-uniform pitch twisted pairs. Finally, the network is combined with the finite difference time domain (FDTD) algorithm to predict crosstalk. In the verification and analysis part of the numerical experiments, on the one hand, the ABAS-BPNN algorithm model is compared with the basic BAS-BPNN algorithm model, the BPNN algorithm model and the GA (genetic algorithm) -BPNN algorithm model, verifying the accuracy and efficiency of the improved BAS-BPNN algorithm. On the other hand, the validity and applicability of the proposed method in crosstalk prediction for non-uniform pitch twisted pair are verified by comparison with the results of the transmission line matrix (TLM) algorithm.

INDEX TERMS Monte Carlo (MC) method, adaptive beetle antennae search (ABAS) algorithm, back propagation neural network (BPNN) algorithm, finite difference time domain (FDTD), non-uniform pitch twisted pair, crosstalk.

I. INTRODUCTION

Among various cables, twisted-pair cables are used in special fields such as robots and aviation because of their superior anti-interference performance [1]. Most scholars have studied the electromagnetic interference caused by field coupling to twisted pairs, but relatively few studies have been conducted on the internal crosstalk of twisted pairs [2], [3]. In fact, the non-uniform pitch of twisted pairs is often caused by the manufacturing process, and the analysis of non-uniform pitch in the existing literature is rare. At the same time, in the face of an increasingly complex electromagnetic environment, twisted pair wires will interfere with the normal operation of other equipment [4]. Therefore, the prediction of non-uniform pitch twisted pair crosstalk has important engineering value and guiding significance.

Based on the idea of cascading, reference [5] firstly proposed a modeling method for twisted pair and analyzed its crosstalk in the frequency domain. Reference [2] assumed that the pitch error is a fixed value to analyze the anti-interference performance of non-uniform pitch twisted pairs, which lacks theoretical randomness. Reference [6] defined the pitch error as obeying a uniform distribution, but most of them obey the normal distribution or approximately obey the normal distribution in engineering practice. Therefore, by analyzing the manufacturing process of twisted pair, this paper defines the manufacturing parameters of twisted pair as a random variable that obeys the normal distribution, and then establishes a mathematical model of non-uniform pitch twisted pair.

For the research of twisted pair crosstalk, the method for analyzing crosstalk of non-uniform multi-conductor transmission line (MTL) can be referred to [7], [8]. In our previous work, based on the cascaded transmission line theory (TLT) combined with the FDTD algorithm, the crosstalk of the...
uniform twisted pair was predicted. At the same time, a parasitic parameter of uniform stranded wire extraction network based on BP neural network algorithm was constructed [9], [10]. However, as the research progressed, the poor robustness of the network was eventually discovered. The BP neural network algorithm relies heavily on its initial weight and threshold parameters, but its initial weight and threshold is randomly generated, which results in a large difference in the results of each simulation and poor robustness [11], [12]. With reference to swarm intelligence algorithms optimizing the BP neural network, the BAS algorithm is introduced to optimize the BP neural network in this paper [13]. Compared with the group optimization algorithm, the BAS algorithm has the advantages of higher convergence rate, simple code, and easy implementation [14]. The BAS-BP fusion algorithm has good stability and applicability, and it solves several problems existing in traditional BP neural network algorithms. This paper also introduces an adaptive factor to improve the reliability of the BAS algorithm, and then uses the fusion algorithm to build a parasitic parameter extraction network for twisted pairs, and then uses MC method to extract the mean of the parasitic parameters of non-uniform pitch twisted pairs [15].

The FDTD algorithm is a numerical method of electromagnetic field based on the cascade idea [16]. Without considering the memory and operation time, the traditional FDTD algorithm can be applied to various situations with almost no restrictions, and can also obtain the solution with higher accuracy [17]. The most important step in the FDTD algorithm solving the crosstalk process is to obtain the per unit length (p.u.l.) parasitic parametric matrix of transmission line [18], [19]. Therefore, this paper uses the FDTD algorithm combined with the above-mentioned p.u.l. parasitic parameter mean matrix of non-uniform pitch twisted-pair to predict the near end crosstalk (NEXT) and far end crosstalk (FEXT) of a specific non-uniform pitch twisted-pair wire, then conducts crosstalk analysis.

Based on the MC idea combined with the ABAS-BP neural network algorithm, this paper proposes a method for estimating crosstalk of non-uniform pitch twisted-pair wires. Firstly, the mathematical model of a non-uniform pitch twisted pair is established in Section II, and a parasitic parameter matrix sample extraction model of twisted-pair wires is also constructed. Section III describes the specific implementation process for predicting non-uniform pitch twisted-pair wires crosstalk. Section IV validates the applicability of the ABAS-BP algorithm based on a specific twisted-pair wires model parameter, and also validates the effectiveness of the new method proposed in this paper for predicting crosstalk. Section V gives the conclusions and outlook of this article.

II. MODELING NON-UNIFORM TWISTED PAIRS

A. MATHEMATICAL MODELING OF NON-UNIFORM PITCH TWISTED PAIR

The twisted-pair wires studied in this paper only have random changes in pitch due to irregular twisting. Their cross-sectional shape does not change and only rotation to the ground exists. This paper models the non-uniform pitch twisted pair based on the principle of twisted pair manufacturing. Fig.1 is a schematic diagram of the principle of making a twisted pair. Each rotation of the shaft $O_1$ increases the length of the twisted pair by $2\pi r$. Twisted wire is twisted once every rotation of shaft $O_2$. The twisted pair is achieved by rotating the shafts $O_1$ and $O_2$. Its mathematical formula is (1) and (2).

$$\begin{align*}
\frac{l}{T_1} &= 2\pi r \ast \frac{t}{T_1}
\end{align*}$$

$$\begin{align*}
\frac{n}{T_1} &= 2\pi \frac{\omega_1}{\omega_2} = F(\omega_1, \omega_2)
\end{align*}$$

where $l$ is the line length, $n$ is the number of pitches, $p$ is the pitch, $\bar{p}$ is the average pitch, and $r$ is the radius of the shaft $O_1$. $T_1$ and $T_2$ are the periods of the shafts $O_1$ and $O_2$ respectively, $\omega_1$ and $\omega_2$ are the angular velocities of the shafts $O_1$ and $O_2$ respectively, $t$ is the production time and is an integer multiple of $T_2/2$.

This article assumes that $\omega_1$ and $\omega_2$ obey normal distributions of $N_1(\mu_{\omega_1}, \sigma_{\omega_1}^2)$ and $N_2(\mu_{\omega_2}, \sigma_{\omega_2}^2)$, respectively. The twisted-pair wires constructed based on this manufacturing
parameter is a non-uniform pitch twisted-pair wire. Fig. 2 is the schematic diagram of non-uniform pitch twisted pair model. Fig. 2(a) is a schematic plan view of a non-uniform pitch twisted pair. Fig. 2(b) is a cross-sectional view of a non-uniform pitch twisted pair. Fig. 3 is a model diagram of the non-uniform pitch twisted pair.

B. TWISTED PAIR PARASITIC PARAMETER MATRIX SAMPLE EXTRACTION MODEL

In [10], the RLCG parameters of the twisted wires change with the twisting of the twisted wires, and this is a non-linear mapping relationship. BP neural network is an intelligent algorithm for dealing with non-linear mapping problems. The mapping relationship shown in formula (3) is established based on the BP neural network algorithm.

\[ [R, L, C, G] = f(\text{degree}) \]  

(3)

where RLCG is the network output, degree is the twist angle of twisted pair, and \( f \) represents the mapping relationship.

In this paper, the twisted-pair twist angle is used as the network input, and the RLCG matrix column vectorized data is used as the output. Based on the analysis of the twisted-pair space structure in previous work [10], this paper uses AnsysQ3d software to extract multiple sets of twisted-pair unit length RLCG parameter samples. When the loss is not considered, the RLCG matrix is a symmetric matrix [4]. Therefore, only the main diagonal and upper triangle elements of the RLCG matrix need to be extracted. As shown in formulas (4) and (5). Vectorising \( R, L, C, G \) matrix data columns to \( Y \).

\[
\begin{align*}
R &= [r_{11}, r_{12}, r_{22}], \\
L &= [l_{11}, l_{12}, l_{22}] \\
C &= [c_{11}, c_{21}, c_{22}], \\
G &= [g_{11}, g_{12}, g_{22}]
\end{align*}
\]  

(4)

\[
Y = [R, L, C, G]^T = [y_1, y_2, \ldots, y_i]^T
\]  

(5)

where \( R, L, C, G \) stands for resistance, inductance, capacitance and conductance parameter matrix respectively.

In general, the influence of \( R \) and \( G \) parameters is ignored because the resistance of the transmission line is much smaller than its termination resistance [4]. Therefore, the BP neural network only trains the \( L \) and \( C \) parameter matrices of the twisted pair. The twisted pair parameter matrix is a second-order matrix, so the total number of training elements is 6, that is \( i = 6 \). Therefore, the neural network is set as a single-input, six-output and single-hidden layer network. Fig. 4 is the topology of the single hidden layer BP neural network.

\[
t = 0.5(m + n) + a, \quad (a = 1, 2, \ldots, 10)
\]  

(7)

where \( a \) is a constant in the interval [1, 10], and the specific value depends on the actual data.

III. REALIZATION OF CROSSTALK PREDICTION FOR NON-UNIFORM PITCH TWISTED PAIR

A. CONSTRUCTION OF MULTIPLE SETS OF NON-UNIFORM PITCH TWISTED PAIRS BASED ON MC ALGORITHM

When applying the MC method, firstly a probability space need to be established, and then determine a random variable \( X \) in this space [15]. The statistics of its distribution function \( F(x) \) is \( g(x) \). Making the mathematical expectation of \( g(x) \) equal to the value \( G \) sought.

\[
E(g) = \int g(x)dF(x)
\]  

(8)

Finally, a simple subsample \((x_1, x_2, \ldots, x_N)\) of the random variable \( X \) is generated. Taking the arithmetic mean \((\bar{G}_N)\) of the statistic \((g(x_1), g(x_2), \ldots, g(x_N))\) as the unbiased estimate of statistic \( g(x) \), as an approximate estimate of \( G(\xi) \).

This article assumes that the normal distributions obeyed by \( \phi_1 \) and \( \phi_2 \) in formula (2) are \( N_1(4\pi/5, 0.1) \) and \( N_2(4\pi, 1) \), respectively. Setting the length of the line in formula (1) to 1 meter, the pitch to 5, the average pitch to 20 cm, the radius to 1/\( \pi \) meters, \( t \) to 1.25 seconds, \( T_1 \) to 2.5 seconds, and \( T_2 \) to 0.5 seconds. Assuming that pitch \( p \) is a random variable that also obeys a normal distribution \( N_3 \). Based on the MC method, the mean value of the normal distribution \( \bar{G} \) was 20 cm, and the standard deviation \( (\sigma_p) \) was 1.82 cm.
number of experiments when solving the mean is 10,000, and the number of experiments when solving the standard deviation is 100,000. Setting the confidence level to 80%, then the 80% pitch falls within the interval of [17.725cm, 22.275cm]. Interval calculation formula at 80% confidence level is formula (9).

\[ p = \bar{p} \pm 1.25 \times \sigma_p \]  

(9)

The five pitches can be any length in the interval, so they are continuously and evenly distributed on the interval. The MATLAB2018 software platform is used to generate random numbers that are uniformly distributed on the interval, and the random numbers are sampled \( N \) times (that is random combinations of unequal length pitch). Taking five random numbers at a time and combine them so that they satisfy formula (10). Each random sampling combination is a non-uniform pitch twisted pair, totaling \( N \) groups.

\[ p_1 + p_2 + p_3 + p_4 + p_5 = 100 \]  

(10)

B. CONSTRUCTION OF TWISTED PAIR PARASITIC PARAMETER EXTRACTION NETWORK BASED ON ABAS-BP NEURAL NETWORK FUSION ALGORITHM

In [10], based on the BP neural network topology of Fig.3 and the sample of the twisted pair parasitic parameter matrix extracted by AnsysQ3d software, the twisted pair parasitic parameter extraction network based on the BP neural network algorithm can be trained and tested to generate the network. However, many existing studies have shown that using an optimization algorithm to optimize the initial weight and threshold of the BP neural network and then training the network can greatly improve the network performance and greatly avoid the random initialization that causes the network to fall into the local optimal problem [20]. The BAS algorithm is a bio-inspired intelligent optimization algorithm, which is derived from the simulation of the beetle predation behavior. Compared with the traditional swarm optimization, this algorithm has a higher convergence rate due to the optimization mode of a single beetle. At the same time, the algorithm has few parameters, strong generality and robustness, and is less subject to initial conditions. Therefore, this paper initially introduces the BAS algorithm to optimize the BP neural network algorithm. The BAS algorithm modeling steps are as follows [14]:

**Step 1:** Assume random orientation of the beetle.

\[
\begin{align*}
\vec{e} &= \frac{\text{rands}(O, 1)}{\text{rands}(O, 1)} \\
\text{rands}(O, 1) &= 2 \times \text{rand}(O, 1) - 1
\end{align*}
\]  

(11)

where \( \text{rand} \) is a random function that generates random numbers between 0 and 1, and \( O \) is the solution space dimension.

**Step 2:** Determine the position of the beetle.

\[
\begin{align*}
x_{i+1} &= x_i + \alpha_i \cdot \vec{e} \cdot \text{sign}(f(x_{i+1}) - f(x_i)) \\
x_i &= x_i - \alpha_i \cdot \vec{e} \cdot \text{sign}(f(x_i) - f(x_i)), \\
\end{align*}
\]  

(12)

where \( x_i \) and \( x_{i+1} \) represent the coordinates of the position of the beetle on the left and right, \( x_i \) is the coordinates of the beetle, \( d' \) is the distance between beards, and \( i \) is the number of iterations.

**Step 3:** Establish fitness function and calculate fitness values \( f(x_i), f(x_{i+1}) \).

**Step 4:** Iterative optimization of the beetle.

In the BAS algorithm, the step size factor controls the convergence speed of the algorithm. The larger the step size factor (toward 1), the slower the convergence speed, but the stronger the global search capability. Conversely, the smaller the factor (toward 0), the faster the convergence speed, but it is easy to fall into local extremes. In order to make the algorithm get better optimization ability, this paper proposes an improved method of dynamically changing the step size factor. Specifically, in the early stage of optimization, in order to expand the overall search space in the solution space and speed up the optimization, a larger step factor should be used. In the later stage of optimization, the search solution tends to be stable. In order to make the solution more accurate, the step size factor should be reduced. In addition, the smaller the initial step size factor, the easier it is to fall into local extremes, so a higher initial value should be given, such as 0.95. Based on the variable step size strategy, an adaptive factor such as formula (14) is set and an adaptive BAS algorithm is finally introduced to optimize the BP neural network algorithm.

\[
\begin{align*}
\alpha_i &= \alpha, \\
\alpha_i &= \alpha - 0.2 \times \left( (i + 1)/(5 \times n) + 0.5 \right), \quad f_i \leq f_{\text{min}} \\
\alpha_i &= \alpha - 0.2 \times \left( (i + 1)/(5 \times n) + 0.5 \right), \quad f_i > f_{\text{min}}
\end{align*}
\]  

(14)

where \( f_i \) is the current fitness value, \( f_{\text{min}} \) is the historical optimal fitness value, \( i \) is the current number of iterations, \( n \) is the total number of iterations, \( \alpha \) is the default step size factor (typically 0.95), and \( \alpha_i \) is the current step size factor.

ABAS-BPNN modeling steps are as follows:

**Step 1:** Assume that the beetle must face random and define the spatial dimension \( O \). Solution space dimensions \( O = 1^*t + t^*6 + t + 6, 1 - t - 6 \) is BP neural network mapping structure.

**Step 2:** Set the adaptive step size factor according to formula (14).

**Step 3:** The root mean square error (MSE) is used as the fitness function. When the fitness value is the smallest, it means that the difference between the predicted output of the network and the true value is the smallest.

\[
\text{MSE} = \frac{1}{N} \sum_{i=1}^{N} (y_i - y_i')^2
\]  

(15)

where \( N \) is the number of samples; \( y_i \) is the network output value of the \( i \)-th sample; \( y_i' \) is the true value of the \( i \)-th sample.
Step 4: Initialize the beetle parameters. Randomly select a random number between \([-0.5, 0.5]\) as the initial parameter, that is the initial coordinates of the day beetle and save it in bestX.

Step 5: The fitness value is calculated according to formula (15) and stored in bestY.

Step 6: Update the left and right beard coordinates of the beetle according to formula (12).

Step 7: Update the beetle position according to formula (13), that is to optimize the weight and threshold of the BP neural network. Calculate the fitness value at the current position and optionally update bestX, bestY.

Step 8: Exit the loop according to the fitness accuracy conditions (this article is set to 0.00002) and the maximum number of iterations (this article is set to 100 generations). If any condition is met, go to step (9), otherwise go back to step (6) to continue for optimization.

Step 9: Generate the optimal solution. When the algorithm stops iterating, the solution in bestX is the training optimal solution, that is the optimal initial weight and threshold of the BP neural network. Based on the initial optimal parameters, a twisted pair RLCG parameter extraction network is constructed.

For a single pitch of a non-uniform pitch twisted pair, each pitch segment is a uniform twisted pair with only one pitch. Based on the above-mentioned proposed twisted-pair parasitic parameter extraction network, it is possible to extract RLCG parameters at any position within any single pitch of a non-uniform pitch twisted pair. Combining N sets of non-uniform pitch twisted pairs based on the MC method, and then using the MC idea, a parasitic parameter mean extraction network of non-uniform pitch twisted pairs is finally constructed.

C. COMBINING FDTD ALGORITHM TO PREDICT NON-UNIFORM PITCH TWISTED PAIR CROSS TALK

Fig.5 is an equivalent circuit diagram of a unit length multi-conductor transmission line. Equation (16) represents the transmission line equation. Based on the idea of cascading, the non-uniform pitch twisted pair is divided into several small segments, each of which is equivalent to a parallel line [7]. The characteristics of the transmission circuit are shown in Fig.5 and formula (16). The RLCG parameter matrix can be obtained from the above extraction network and the transmission equation can be solved by using the FDTD method.

\[
\begin{align*}
\frac{\partial}{\partial z} V(z, t) &= -R(z)I(z, t) - L(z) \frac{\partial}{\partial t} I(z, t) \\
\frac{\partial}{\partial z} I(z, t) &= -G(z) V(z, t) - C(z) \frac{\partial}{\partial t} V(z, t)
\end{align*}
\]  

(16)

where \(V(z, t)\) and \(I(z, t)\) are the voltage and current of the circuit with respect to \(z\) and \(t\), respectively. \(R(z)\), \(L(z)\), \(C(z)\) and \(G(z)\) are the circuit parasitic parameter for \(z\).

Discretize the length of time and length of space by using type \(\pi\) discrete form. Making the voltage node at the position where the time step of integer multiples and the space step of integer multiples meet, and the current node at the position where the time step of half integer multiples and the space step of half integer multiples, as shown in formula (17) [18]. The calculation sequence using center difference approximation is shown in Fig. 6.

\[
\begin{align*}
I_{k+1/2}^{n+1/2} &\equiv I((n+1/2)\Delta t, (k+1/2)\Delta z), \quad k = 0, 1, \ldots, k-1 \\
V_{k}^{n+1/2} &\equiv V((n+1/2)\Delta t, k\Delta z), \quad k = 0, 1, \ldots, k
\end{align*}
\]  

(17)

where \(n\) is the number of time segments and \(k\) is the number of space segments.

With the influence of \(R\) and \(G\) ignored, the central difference approximation to formula (16) according to the voltage and current calculation sequence shown in Fig. 6 can be used to obtain formula (18). By using formula (18), the recursive relationship between the voltage and current nodes on the transmission line to be solved can be derived as formula (19). Fig. 7 is a block diagram of an overall crosstalk prediction process. From the data collection and processing to the data training test, the RLCG mean parameter is finally obtained based on the MC method. By bringing this parameter into the FDTD algorithm, the prediction of crosstalk can be achieved.

\[
\begin{align*}
\frac{V_{k+1}^{n+1/2} - V_{k}^{n+1/2}}{\Delta z} + L(z) \frac{I_{k+1/2}^{n+1/2} - I_{k-1/2}^{n+1/2}}{\Delta t} &= 0 \\
\frac{I_{k+1/2}^{n+1/2} - I_{k-1/2}^{n+1/2}}{\Delta z} + C(z) \frac{V_{k+1/2}^{n+1} - V_{k-1/2}^{n+1}}{\Delta t} &= 0
\end{align*}
\]  

(18)
\[
\begin{align*}
I_{n+1/2}^{k+1/2} &= \left( \frac{L(z)}{\Delta t} \right) I_{n-1/2}^{k+1/2} - \frac{V_{n+1}^{k+1} - V_{n-1}^{k+1}}{\Delta z} \left( \frac{L(z)}{\Delta t} \right)^{-1} \\
V_{n+1}^{k+1} &= \left( \frac{C(z)}{\Delta t} \right) V_{n-1}^{k+1/2} - \frac{I_{n+1/2}^{k+1} - I_{n-1/2}^{k+1}}{\Delta z} \left( \frac{C(z)}{\Delta t} \right)^{-1}
\end{align*}
\] (19)

where \( n = 0, 1, \ldots, N, k = 0, 1, \ldots, K \).

### IV. VERIFICATION AND ANALYSIS

#### A. VALIDATION TEST OF ABAS-BPNN ALGORITHM

This paper improves the twisted-pair parasitic parameter extraction algorithm proposed in [10] and uses ABAS algorithm to optimize the BP neural network algorithm to build a twisted-pair parasitic parameter extraction network. In fact, the extraction network is also applicable to the multi-core stranded wire model. To further verify the effectiveness of the algorithm, a specific twisted pair is used as an example to illustrate the performance of the new method. Twisted pair single wire uses copper wire with polyvinyl chloride (PVC) insulation layer, and different core wires are spirally wound counterclockwise. The twisted-pair wires are placed at the same height in a space 8 mm above the ground. The specific parameters of the twisted pair are shown in Table 1.

Due to the axis symmetry of the twisted wires, the RLCG parameter matrix within 1/2 pitch as shown in Fig.8 to obtain the RLCG parameter matrix within the entire pitch. Starting from 0°, the \( R, L, C \), and \( G \) parameter matrix samples were collected once for twisted pairs within 1/2 pitch at an equal interval of 5°, and ended at 175°, with a total of 36 sets of data. In the experiments of this paper, according to the empirical formula of hidden layer neurons (7) and the method of repeated experiments, it is determined that the hidden layer neuron \( t = 9 \), and the training error accuracy of the neural network is set to \( E_{\min} = 10^{-6} \). The initial step size of the beetle is \( C = \sqrt{O} \), and the solution space dimension \( O \) is 78.

After randomly arranging 36 groups of data, the next 12 groups are selected as the test data, corresponding to the y-coordinates in Fig.9, whose 1 to 12 represent 10°, 135°, 80°, 170°, 160°, 120°, 105°, 125°, 60°, 85°, 15°, 25°. Fig.9 is a histogram of test error distribution. Fig.9 shows that the maximum test error of the test data does not exceed 0.0015,

| Name                      | Parameter         |
|---------------------------|-------------------|
| wire diameter             | 0.5mm             |
| insulation layer thickness| 0.8mm             |
| insulation material       | 2.7               |
| length                    | 1000mm            |
| height                    | 8mm               |
| single wire conductivity  | 5800000 S/m       |
| number of cores           | 2                 |

#### TABLE 1. Basic parameters.
Table 2. Comparison of different models.

| model        | Mean error | Maximum error | CPU time/s |
|--------------|------------|---------------|------------|
|              | L          | C             |            |
| ABAS-BPNN    | 4.5e-4     | 3.2e-4        | 0.0015     | 50.268251 |
| BPNN         | 0.0105     | 0.0014        | 0.0239     | 11.537913 |
| BAS-BPNN     | 0.0013     | 0.0012        | 0.0080     | 48.696871 |
| GA-BPNN      | 0.0019     | 3.6e-4        | 0.0090     | 470.707882 |

and the average value of the test error is only 3.8333e-4, and the prediction accuracy is good. The formula for calculating the test error according to formula (15) is as follows:

$$E_{test} = \frac{y_i - y_i'}{y_i'}, (i = 1, 2, \ldots, n)$$  \hspace{1cm} (20)

At the same time, in order to illustrate the high-precision performance of this model, this paper compares it with the BPNN model in [10], BAS-BPNN model and the GA-BPNN model representing the optimized BPNN of the group algorithm. Selecting the relative error evaluation index and CPU running time to evaluate the performance of the model. Formula (21) is the formula for calculating the absolute value of relative error. The model comparison results are shown in Table 2.

$$E_i = \frac{|y_i'' - y_i'''|}{y_i''}, (i = 1, 2, \ldots, n)$$  \hspace{1cm} (21)

where $E_i$ is the relative error, $y_i''(i = 1, 2, \ldots, n)$ is the predicted value of the i-th sample; $y_i'''(i = 1, 2, \ldots, n)$ is the true value of the i-th sample; n is the number of samples. The smaller the relative error, the shorter the CPU running time, and the better the performance of the characterization model.

It can be seen from Table 2 that the estimation effects of the four models on the capacitance matrix are all good, but the ABAS-BP neural network algorithm is obviously more accurate. When estimating the inductance matrix, the accuracy of the traditional BP neural network algorithm used in [10] is much worse than that of the other three models. From the perspective of overall estimation accuracy and convergence speed, the ABAS-BP neural network algorithm works best. It not only verifies the effectiveness of the ABAS-BPNN algorithm, but also it is a good improvement on the method of extracting the parasitic parameters of the stranded wire in [10].

B. CROSSTALK ANALYSIS EXPERIMENT

The non-uniform pitch twisted pair RLCG parameter matrix extraction method based on the MC method, the ABAS-BP neural network and the FDTD algorithm are used to calculate its crosstalk, which is called the new method here. The old method in this article refers to the use of modulus decoupling to solve crosstalk. The TLM algorithm is a high-precision numerical calculation method of electromagnetic field [21], which has high reference value. The crosstalk result obtained by this method is used as a reference standard, and is called exact solution here. The simulation experiment platform shown in Fig.10 is constructed, and the terminal is connected to a 50ohm resistor, and the line 1 is connected to an excitation source, and the excitation source is a sinusoidal voltage of 1V.

According to the parameters in Table 1, the non-uniform pitch twisted pair crosstalk is solved by three methods in the frequency band of 100kHz-1GHz. The obtained crosstalk results are shown in Fig.11 and Fig.12.

Fig.11(a) shows the NEXT of the non-uniform pitch twisted pair solution solved by three methods. The solid blue line is a randomly generated non-uniform pitch twisted pair for CST (TLM) simulation, which is used as the reference standard in this article. The yellow dotted line is the average NEXT of the non-uniform pitch twisted pair estimated by the method proposed in this paper. Its crosstalk is $-57.832$dB at 100kHz, which is $0.642$dB different from the simulation results. Then it rose steadily in the middle and low frequency bands, which basically coincided with the results of simulation experiments. It reflected a higher prediction accuracy. High-frequency crosstalk swings up and down at $-15$dB. The red dotted line represents the result of the modulus decoupling method, which is $-60.395$dB at 100kHz, which is $3.204$dB different from the simulation experiment result. It is roughly 2 to 3 dB worse than the simulation experiment results in the whole frequency band, some frequency points are too different, which shows the estimation accuracy is average.

Fig.11(b) shows the FEXT results obtained by the three methods. The method proposed in this paper solves crosstalk at $-60.228$dB at 100kHz, which is $0.356$dB different from the simulation results. After that, it rises steadily in the low and middle frequency bands and swings up and down at $-10$dB in the high frequency bands. The result of modulus decoupling is $-61.899$dB at 100kHz, which is $2.031$dB different from the simulation result. It can be seen from the figure that the FEXT solved by the method proposed in this paper shows high accuracy in all frequency bands.

In order to further analyze the crosstalk results in the high frequency band, this article enlarges the crosstalk results in the 500MHz to 1GHz frequency band, as shown in Fig.12. Fig.12(a) and Fig.12(b) are the amplified high-frequency NEXT and FEXT results, respectively. The solid blue line is the result of simulation experiments and the solid red line is the result of the method proposed in this paper. Regardless of the analysis of NEXT or FEXT, the method and simulation.
results presented in this paper are basically not shifted in frequency. As far as the value of crosstalk is concerned, the NEXT results show a large difference of about 18dB at about 550MHz, and there is not much difference at other frequencies. The FEXT results show a difference of about 8dB at about 820MHz, and there is not much difference at other frequencies.

In general, crosstalk analysis experiments have basically verified the applicability of the new method proposed in this paper to the estimation of crosstalk in non-uniform pitch twisted pairs. However, in the high frequency band, the results of the new method and the simulation experiment are still different, which may be caused by the following two reasons. First, the number of segments of the FDTD algorithm in this paper is only 150 segments. As the number of segments increases, the actual twisting effect can be more and more expressed, and the accuracy of the estimation crosstalk will also be higher. Secondly, the new method proposed in this paper solves the mean of crosstalk, which should be different from that of a specific non-uniform pitch twisted pair. However, because the standard deviation of the new method

for solving crosstalk and the average value of crosstalk are not on the same order, the average crosstalk can represent the crosstalk of the non-uniform pitch twisted pair model constructed in this paper. The crosstalk results in the low and middle frequency bands in the experiment also show the effectiveness of the mean crosstalk.

V. CONCLUSION

This paper improves the method for extracting the RLCG parameters of the twisted pair proposed in [10], which not only has higher accuracy and robustness, but also can extract the parasitic parameters of non-uniform pitch twisted pairs. Also, based on improved model extraction of high-precision twisted-pair RLCG parameters and the MC idea, this paper proposes a new method for estimating non-uniform pitch twisted-pair crosstalk. Numerical experiments verify that the new method shows good applicability and effectiveness. Especially the high consistency in the low and middle frequency bands shows that the average crosstalk obtained by the new method represents the overall crosstalk with high accuracy. The estimation results of non-uniform pitch twisted pair crosstalk can provide important guiding significance and reference value for electromagnetic compatibility design in engineering practice. Finally, compared with the ABAS algorithm, the beetle swarm algorithm can handle higher-dimensional objective functions. The upwind differential algorithm based on flux splitting has higher efficiency than traditional FDTD algorithm. Future research on these two aspects will also have important significance.

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