Optimization of Shielding Electrode and Inner Shielding Structure for UHV Oil-gas Bushings with Improved Hybrid Algorithm Combining Particle Swarm Optimization and Back-Propagation Neural Network

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Abstract. With the development of prototype for UHV oil-gas bushings, E-field distribution around bushing end and structure optimization for shielding electrode is an important issue to be studied. The basic principles and processes of hybrid algorithm combining particle swarm optimization and back-propagation neural network (PSO-BP algorithm) has been discussed in this paper. The optimization capability and accuracy of proposed algorithm has been verified with continuous explicit function. The structure optimization of shielding electrode has been conducted using PSO-BP algorithm. The study shows that PSO-BP algorithm can seek extreme point of testing function exactly, and jump over trap of local optimal solution; three-dimensional full model of bushing is needed in E-field distribution calculation; PSO-BP algorithm has found the best structure parameters of shielding electrode, with which more even E-field distribution can be obtained, and maximum electric strength can be reduced by 64.9%, moreover, the computing time is about 75.2% less than traditional PSO algorithm. The study results have been applied in bushing prototype manufacture which has passed through all testing experiments. The optimization method proposed in the paper can also be used in optimization design for other complex insulation structures.

1. Introduction

High voltage bushing is the key equipment in power system. When the high voltage current carrying conductor passes through the metal box or wall which is different from its potential, the bushing can effectively reduce the concentration of electric field. In various kinds of bushing, capacitance type bushing are widely used in the super high voltage and ultra-high voltage levels. The type of bushing is equipped with capacitor core between guide rod and flange, and there are multilayer metal plates inside the sleeve to force the electric field inside and outside the sleeve to be uniform. On the other hand, the construction of super high voltage and UHV substations in China is rapid, and the land resources and environmental problems are increasingly prominent. Compared with the ordinary oil to air type bushing connecting the overhead soft conductor, the oil-gas sleeve connecting transformer and the fully enclosed combined electrical apparatus have great advantages in terms of reliability, floor area and other technical indexes. Therefore, the development of UHV capacitance oil and gas bushing is carried out in China Work[1,2]. The capacitance oil and gas bushing is a typical complex insulation structure, especially in the UHV level, the reasonable design is very important for the safe and stable operation of the bushing. A large number of field operation experience shows that the flash-over and
explosion of bushing usually originate from internal corona discharge, while corona discharge mainly occurs at the connection fittings at the end of the bushing, so it is necessary to configure reasonable equalizing ball to avoid local electric field concentration. In view of this, the electric field simulation and optimization of the structure of the UHV oil and gas bushing are carried out.

In the early literature, the charge simulation method (CSM) was generally used to analyze the surface electric field distribution of the grading ball through the simplified model of the bushing, but for the complex insulation structure of the bushing, the calculation results are quite different from the actual situation[3-5]. With the development of electromagnetic field numerical calculation technology, the finite element method (FEM) can effectively consider the influence of the structure of the pressure sharing sphere outer sleeve on its electric field distribution, but it has higher requirements on the calculation hardware and time[6,7]. At the same time, the traditional optimization method of the structure of the bushing grading ball is to adjust the parameters of the outer contour of the grading ball through the iterative calculation of the surface electric field until it meets the requirements of precision control. However, this method has the disadvantages of slow convergence speed and weak universality. Through the above analysis, it can be seen that the difficulties of the optimization are as follows: 1) make the simulation results of the electric field on the surface of the bushing grading ball consistent with the actual situation as far as possible; 2) shorten the optimization time of the grading ball structure as far as possible, and the optimization algorithm has high search accuracy and iterative efficiency. Considering that BP(back propagation) neural network has been used in high voltage electrode electric field optimization, its high nonlinear mapping ability effectively solve the problem of long finite element calculation time. The particle swarm optimization (PSO) is a popular and fast developing artificial intelligence algorithm, which has the advantages of good optimization effect and strong convergence characteristics. Based on this, this paper continues to study and analyze structure optimization of the bushing pressure equalizing ball from the following three aspects: ① using the improved PSO algorithm to optimize the weights and thresholds of neural network, improve the nonlinear prediction accuracy of fitness function, and search the optimal value of fitness function through PSO algorithm; ② using large-scale finite element analysis to improve the three-dimensional finite element calculation model of bushing corona equalizing ball; ③ the BP neural network is used to realize the nonlinear fitting between the structure parameters and the independent variables of fitness function, and finally the trained neural network is used to replace the finite element electric field simulation to shorten the optimization calculation time[8-12].

In this paper, taking the AC UHV oil and gas bushing voltage equalizing ball as the research object, the PSO optimization neural network and the optimal value search algorithm are introduced in detail. The three-dimensional simulation calculation of the surface electric field of the pressure equalizing ball is carried out by using calculation platform, and the optimization design process of the pressure equalizing ball structure by using the improved particle swarm optimization neural network hybrid algorithm (PSO-BP algorithm). The results show that this method can effectively realize the structure optimization of bushing pressure balancing ball, and has the characteristics of fast calculation speed, high degree of automation and strong optimization ability. The research results of this paper have been successfully applied to the trial production of UHV oil and gas bushing prototype, and have certain reference value for the research of PSO-BP algorithm in the field of power system insulation structure optimization design.

2. Improved particle swarm optimization neural network hybrid algorithm and numerical verification

2.1. Construction of BP neural network
In 1974, P. Werbos put forward the first learning algorithm suitable for multi-layer network. The neural network trained by this algorithm is called BP neural network. In the practical application of artificial neural network, 80%~90% of them adopt BP network or its variation form. Therefore, this
paper adopts multi-layer BP neural network to optimize the structure of bushing pressure equalizing ball, and its topological structure is shown in Figure 1.

In Figure 1, \( R \) is the dimension of the input vector \( P \) of the neural network, \( S \) is the number of neurons in the hidden layer, and \( t \) is the number of neurons in the output layer. \( W_1 \) and \( b_1 \) are the connection weights and thresholds of hidden layer, which can be expressed as \( W_{ij}(i=1,2,...,S, j=1,2,...,R) \) and \( b_i(i=1,2,...,S) \). Similarly, \( W_2 \) and \( b_2 \) are connection weights and thresholds of output layer, which can be expressed as matrix type \( W_{mn}(m=1,2,...,t, j=1,2,...,S) \) and \( b_m(m=1,2,...,S) \). The hidden layer and the output layer use logsig and purelin excitation functions respectively.

\[
\begin{align*}
\logsig(x) &= \frac{1}{1 + e^{-x}} \\
p &= \logsig(W_1p + b_1) \\
\end{align*}
\]

\[
\begin{align*}
\text{purelin}(x) &= x \\
a_2 &= \text{purelin}(W_2a_1 + b_2) \\
\end{align*}
\]

\( X \) is the input of single neuron and \( f(x) \) is the output of neuron. The practice shows that for the general nonlinear prediction problem, the above-mentioned excitation function configuration will have higher prediction accuracy. The learning process of BP neural network consists of forward propagation and back propagation: in the process of forward propagation, the input vector \( p \) is processed by the input layer and hidden layer layer by layer and then transmitted to the output layer. If the predicted output of the network is \( O_k(k=1,2,...,t) \), the expected output is \( Y_k(k=1,2,...,t) \), then the network prediction error \( e_k(k=1,2,...,t) \) can be expressed as:

\[
e_k = Y_k - O_k
\]

According to the \( e_k \) in (3), the network connection weights \( W_{ij} \) and \( W_{mn} \), and the network thresholds \( b_i \) and \( b_m \) are continuously updated:

\[
\begin{align*}
W_{ij} &= W_{ij} + \eta a_{ij}(1-a_{ij})pP \sum_{k=1}^{t} W_{jk}e_k \\
W_{mn} &= W_{mn} + \eta a_{mn}e_k \\
b_i &= b_i + \eta a_{ij}(1-a_{ij})P \sum_{k=1}^{t} W_{jk}e_k \\
b_m &= b_m + e_k \\
\end{align*}
\]

In the formula, \( \eta \) is the learning rate, which is calculated by the formula (4) \sim (5) until the prediction error \( e_k \) meets the accuracy control requirements. In this paper, the electric field distribution on the surface of the bushing grading ball will be obtained by finite element calculation. In order to combine with the finite element solution, the prediction point will be selected as the finite element node of the grading ball calculation area. For UHV bushing, the size of equalizing ball is large, and in order to obtain the surface electric field distribution accurately, the dense grid is needed, so the number of input and output samples is large, and the structure of neural network used for training is complex. In this case, if the traditional BP error correction algorithm is used, it is easy to fall into the local optimal value and difficult to converge to the set accuracy in the network training process.
Therefore, this paper combines PSO algorithm with BP neural network to obtain the optimal weights and thresholds of the network, and further improves the prediction accuracy of neural network[13-16].

2.2. Basic process of PSO-BP optimization algorithm

The particle swarm optimization (PSO) is inspired from the behavior characteristics of the biological population and used to solve optimization problems. In the algorithm, each particle represents a potential solution of the problem, and each particle corresponds to the fitness value determined by fitness function \(F\). Particle velocity determines the moving direction and distance of particles, and the velocity is dynamically adjusted with the moving experience of itself and other particles, so as to realize the individual optimization in the solvable space[17-20]. Suppose that in a \(D\)-dimensional search space, the population is composed of \(n\) particles, in which the \(i^{th}\) particle is expressed as a \(D\)-dimensional vector, representing the position of the \(i^{th}\) particle in the \(D\)-dimensional search space. According to the objective function \(f\), the fitness value of each particle position can be calculated. The velocity of the \(i^{th}\) particle is

\[
V_{id}^{k+1} = \omega V_{id}^k + c_1 r_1 (P_{id}^k - X_{id}^k) + c_2 r_2 (P_{gd}^k - X_{id}^k)
\]

(6)

and the global extremum of the population is \(P_g = (P_{g1}, P_{g2}, ..., P_{gd})^T\). In each iteration, the particle updates its velocity and position through the individual extreme value and global extreme value.

\[
V_{id}^{k+1} = \omega V_{id}^k + c_1 r_1 (P_{id}^k - X_{id}^k) + c_2 r_2 (P_{gd}^k - X_{id}^k)
\]

(6)

Where, \(\omega\) is inertia weight, \(d=1,2,...,n\); \(k\) is the current number of iterations; \(c_1\) and \(c_2\) are non negative acceleration factors; \(r_1\) and \(r_2\) are random numbers distributed between [0,1]. In order to balance the global search and local search ability of PSO algorithm, this paper uses linear decreasing inertia weight:

\[
\omega(k) = \omega_{start} - (\omega_{start} - \omega_{end})k/T_{max}
\]

(7)

In the above formula, \(\omega_{start}\) is the initial inertia weight (generally 0.9); \(\omega_{end}\) is the inertia weight when iterating to the maximum number (generally 0.4); \(T_{max}\) is the maximum number of iterations. For the optimization of neural network weights and thresholds, the fitness function \(f\) can be described by

\[
f = \sqrt{\sum_{k=1}^{n} (Y_k - O_k)^2}
\]

(8)

If the function \(f\) is absolutely zero, the neural network has the optimal weight and threshold, The number of optimization variables \(N_t\) is:

\[
N_t = RS + St + S + t
\]

(9)

Formula (9) shows that when the input \(R\) is large, there are many optimization variables, which can make full use of the ability of global search and multi-objective optimization of PSO algorithm.

2.3. Numerical verification of PSO-BP optimization algorithm

In order to analyze the convergence rate and global optimization performance of PSO-BP optimization algorithm, three kinds of functions are used for verification. The main purpose is: ① to compare the performance of the traditional BP neural network and PSO optimization neural network in nonlinear function fitting; ② to evaluate whether the PSO-BP optimization algorithm can effectively find the optimal solution of objective function and investigate the optimization accuracy. The expression of the test function and the range of independent variables are listed in Table 1. For function \(f_1\), 500 groups of data are randomly generated, 400 groups are used for BP neural network learning and nonlinear fitting, and 100 groups are used for testing. The PSO-BP algorithm fits the function \(f_1\) well, as shown in Figure 2.
Fig. 2 Function fitting for $f_1$ with PSO-BP

Fig. 3 Comparison between PSO-BP and BP algorithm

Fig. 4 Convergence curves with PSO

PSO algorithm optimized BP neural network and traditional network are used to test 100 groups of data. The comparison results are shown in Figure 3. It can be seen that PSO-BP algorithm controls the prediction error near zero, while the BP error correction algorithm has large prediction error and significant jump[21-22]. On the basis of network optimization, the PSO algorithm and trained neural network are used to optimize the extremum of functions $f_1$, $f_2$, $f_3$. The results are shown in Table 2. For function $f_1$, the convergence process of PSO neural network optimization and function extremum optimization fitness function is shown in Figure 4.

### Tab.1 Testing functions for PSO-BP

| Function name | Function form | Variable range |
|---------------|---------------|----------------|
| $f_1$         | $4x_1^2 - 2.1x_1^4 + \frac{1}{3}x_1^6 + x_1x_2 - 4x_2^2 + 4x_2^4$ | $[-5,5]$ |
| $f_2$         | $\sum_{i=1}^{6} x_i^2$ | $[-5,5]$ |
| $f_3$         | $\sum_{i=1}^{6} [x_i^2 - 10 \cos(2\pi x_i) + 10]$ | $[-5.12,5.12]$ |

### Tab.2 Test results of PSO-BP algorithm

| Function name | Search extremum | Theoretical extremum |
|---------------|-----------------|----------------------|
| $f_1$         | -1.0316274      | -1.0316285           |
Table 2 shows that PSO-BP algorithm can better search the extreme value of test function, and can achieve high accuracy. The function \( f_2 \) is a multi parameter optimization problem, and the effective search of the function extremum indicates that the algorithm has the ability to quickly move to the multi-objective function extremum. The test function \( f_3 \) is a highly multimodal function, which has a large number of local optima. The successful acquisition of the function extremum proves that the algorithm has advantages in getting rid of the local optima. At the same time, PSO-BP algorithm does not depend on the specific function expression, only needs the specific data as the training sample to complete the learning of BP neural network, which is suitable for the structure optimization research of UHV bushing pressure equalizing ball in this paper, because the surface field strength distribution of pressure equalizing ball is discrete data points, which cannot be directly represented by explicit continuity function.

2.4. Principle and implementation of hybrid algorithm of RBF neural network and NSGA-II

Radial basis function (RBF) is a traditional technique of multidimensional spatial interpolation, which was proposed by Powell in 1985. RBF neural network belongs to three-layer forward network type. Its basic idea is to use RBF as the "base" of hidden unit to form hidden layer space. The hidden layer transforms the low dimensional pattern input data into the high dimensional space, so that the linear inseparable problem in low dimensional space is linearly separable in high dimensional space. The activation function of RBF neural network takes the distance between the input vector and the weight vector as the independent variable[19-21]. The general expression of activation function of RBF neural network is as follows:

\[
R(||\text{dist}||) = e^{-||\text{dist}||^2}
\]  

With the decrease of the distance between the weight and the input vector, the output of the network increases. When the input vector and the weight vector are consistent, the output of the neuron is 1, and the threshold \( b \) is used to adjust the sensitivity of the neuron. The RBF neural network learning algorithm needs to solve three parameters: the center and variance of the basis function, and the weight from the hidden layer to the output layer. The commonly used radial basis function in radial basis function neural network is Gaussian function, so the activation function of radial basis function neural network can be expressed as:

\[
R(x_p - c) = \exp\left(-\frac{1}{2\sigma^2} ||x_p - c||^2\right)
\]

Where \( ||x_p-c|| \) is the Euclidean norm; \( c \) is the center of Gaussian function; \( \sigma \) is the variance of Gaussian function. According to the structure of radial basis function neural network, the output of the network is as follows:

\[
y_i = \sum_{j=1}^{h} \omega_j \exp\left(-\frac{1}{2\sigma^2} ||x_p - x_i||^2\right) j = 1, 2, ..., n
\]

Where \( x_p = (x^p_1, x^p_2, ..., x^p_m)^T \) is the \( p \)th input sample; \( p = 1, 2, 3, ..., P \), \( P \) are the total number of samples; \( c_i \) is the center of hidden layer node; \( w_j \) is the connection weight from hidden layer to output layer; \( i = 1, 2, 3, ..., h \) is the number of hidden layer nodes; \( y_j \) is the actual output of the \( j \)th output node of the network corresponding to the input sample. Let \( d \) be the expected output value of the sample:

\[
\sigma = \frac{1}{P} \sum_{j} ||d_j - y_j c_i||^2
\]

The specific steps of the learning algorithm are as follows:

① Network initialization: randomly select \( h \) training samples as the clustering center \( c(i=1, 2, ..., h) \);
The input training samples are grouped according to the nearest neighbor rule: \( x_p \) is assigned to each cluster set of input samples according to the euclidean distance between \( x_p \) and \( \mathcal{S}_p \) (\( p=1,2,\ldots,P \));

Readjust the clustering center: calculate the average value of training samples in each clustering set, that is, the new clustering center \( c_i \). If the new clustering center no longer changes, the obtained \( c_i \) is the final basis function center of RBF neural network, otherwise, return to ② for the next round of center solution. The basis function of the RBF neural network is Gaussian function, and the variance can be solved by the following formula:

\[
\sigma_i = \frac{c_{\text{max}}}{\sqrt{2h}} \quad i=1,2,\ldots,h
\]

In equation (14), \( C_{\text{max}} \) is the maximum distance between the selected centers. The connection weights between the hidden layer and the output layer can be directly calculated by the least square method

\[
\omega = \exp\left(-\frac{h}{c_{\text{max}}} \| x_p - c_i \| \right) \quad i=1,2,\ldots,h; p=1,2,3,\ldots,P
\]

2.5 Numerical verification of hybrid algorithm of RBF neural network and NSGA-II

Before using the above hybrid algorithm to optimize the inner shielding structure of UHV through wall bushing, the explicit function is used to verify the algorithm. The following is the multi-objective optimization solution for the two objective functions of (16) - (17).

\[
\begin{align*}
\begin{cases}
    f_1(x) = x^3 \\
    f_2(x) = \sin(2\pi x)
\end{cases}
\end{align*}
\]

Equation (16) has one optimization variable and two optimization objective functions with the independent variable range of \([-5,5]\]; while the equation (17) has two optimization variables and two optimization objective functions with independent variable range of \([-1,1]\). For the explicit function with the analytic solution, step 1) can be omitted, and sample plane of formula (16) and formula (17) can be reconstructed directly by RBF neural network. The reconstruction effect is shown in Figure 5.
Figure 6 shows RBF neural network can perform better function reconstruction for one-dimensional function (16) and two-dimensional function (17). The value of the key points calculated by the original function is basically equal to the value calculated by RBF neural network, and the strong interpolation and extrapolation ability of RBF neural network can be used to calculate the value beyond the key points, which is conducive to the multi-objective optimization of the objective function, because the trained RBF network can replace the calculation of the original function, and the RBF neural network does not need too much. The interpolation and extrapolation results are good.

In order to verify the feasibility and effectiveness of the hybrid algorithm of RBF neural network and NSGA-II in multi-objective optimization, this paper continues to use the test functions (16) and (17) to verify the algorithm: 1) the original function is substituted into NSGA-II algorithm for direct multi-objective optimization; 2) the trained RBF neural network and NSGA-II are mixed to complete multi-objective optimization, and the multi-objective optimization in both cases is realized. The results are compared, as shown in Figure 6. In the graph, the test function is randomly selected, and the optimal solution set is a part of the random value, that is Pareto solution set. By comparison, it is found that the Pareto solution sets obtained in the two cases basically coincide, which shows hybrid algorithm of RBF and NSGA-II can find the Pareto solution set better.

Compared with other algorithms, the hybrid algorithm of RBF neural network and NSGA-II has some advantages for the optimization of inner shielding structure of UHV through wall bushing. Because it is necessary to use the finite element method to calculate the field strength at each key position of the inner shielding layer, and this process takes a long time to calculate. If the training samples of RBF neural network can be obtained through a certain number of finite element calculation, and then the trained RBF neural network can be used in NSGA-II algorithm for multi-objective optimization, a lot of finite element calculation time can be saved and better optimization effect can be obtained.

3. Hybrid algorithm for inner shielding structure optimization of UHV wall bushing

Through the above finite element simulation, it is found that the shielding structure parameters of UHV wall bushing directly determine the electric field strength at the key position. For the double-layer shield structure (grounding shield and intermediate shield) studied in this paper, five structural parameters are defined through analysis: $D_1$ and $L_1$, which can determine the overall size of the intermediate shield. $D_2$ and $L_2$, which can determine the overall size of the grounding shield; $L$, which can determine the relative position of the double-layer shield, as shown in Figure 7. The optimization goal mainly includes two aspects: the field strength value at the key position should be as small as possible under the condition of meeting the control requirements. The volume of the internal shielding structure should be as small as possible to reduce the volume of bushing. Obviously, when the volume
of the shielding cylinder shrinks, its surface field strength will increase, so the above optimization objectives are contradictory. Through the above analysis, it can be seen that the hybrid multi-objective optimization algorithm of RBF neural network and NSGA-II proposed in this paper is suitable for the optimization of the internal shielding structure. Before using NSGA-II algorithm for multi-objective optimization, RBF neural network is needed to reconstruct the corresponding relationship between structural parameters and field strength values at key positions. To realize network reconstruction, an appropriate amount of the original data is needed as training samples. The variation range of five structural parameters of through wall bushing is determined as shown in Table 3.

| Tab.3 Optimization parameters of inner shielding |
|------|------|------|------|------|
| Parameter |  $D_1$ |  $D_2$ |  $L_1$ |  $L_2$ |  $L$ |
| Range (mm) | 280–640 | 660–880 | 4000–5000 | 1500–2000 | 400–1000 |

The specific size of shield in the wall bushing is determined according to five structural parameters randomly within the range of the structural parameters. The electric field strength of the bushing is calculated by finite element method. The electric field strength values at the key positions of the shield in the bushing are extracted, including the maximum field strength $E_1$ on the surface of the central guide rod, the maximum field strength $E_2$ on the middle shield surface, the maximum field strength $E_3$ on the ground shield surface, and the maximum field strength $E_4$ of composite insulator jacket. In order to optimize the multi-objective by the using RBF neural network and NSGA-II hybrid algorithm, $E_i$ ($i=1~4$) is taken as the objective function, and the control value of field strength of inner shield is taken as 20kV/mm, and the control value of composite coat is taken as 0.9kV/mm. Therefore, the multi-objective optimization problem can be described by formula (18):

$$
\begin{align*}
\min & : E_i = f_i(\vec{X}) \\
\text{s.t.} & \begin{cases} 
E_i < 20kV/mm & (i = 1, 2, 3) \\
E_4 < 0.9kV/mm \\
\vec{X}_{\min} < \vec{X} < \vec{X}_{\max}
\end{cases}
\end{align*} 
$$

(18)

Among them, $\vec{X} = (D_1, D_2, L_1, L_2, L)$. In order to obtain enough training samples of the RBF neural network, 3500 times of the random calculation are carried out, of which 3400 samples are used for learning and training of RBF neural network, and the remaining 100 samples are used to verify the training effect and the prediction accuracy of the RBF neural network. Figure 7 shows 3500 sets of calculation results of the maximum field strength $E_3$ of intermediate shielding surface (the maximum field strength at other locations is omitted due to space limitation). It can be seen from the figure that the maximum field strength $E_3$ of the middle shielding surface varies from 9.5kV/mm to 14.5kV/mm, and the field strength is randomly distributed, which is ergodic in the whole parameter variation range. In order to verify the prediction accuracy of trained RBF neural network, 100 groups of finite element calculation values and prediction values in the verification samples are listed in Figure 8. It can be seen from the figure that the two are basically consistent, indicating that RBF neural network has high prediction accuracy, and the high-precision RBF prediction neural network is the basis of NSGA-II algorithm for multi-objective optimization.
Considering the calculation time, it only takes about 0.8s to input the shielding structure parameters into the RBF neural network and output the field strength at each key position, but the maximum field strength at each key position is about 25s by the finite element calculation, which shows that the calculation time is greatly reduced and the calculation accuracy is not lost. It can be seen from Figure 8 that the maximum field strength values of the inner center guide rod and the middle shield are both high, so in the multi-objective optimization, the two maximum field strength values are taken as the optimization objectives. The trained RBF neural network and NSGA-II hybrid algorithm are used for dual objective optimization, in which the population number is set to 400. After about 200 iterations, the Pareto optimal solution set under the dual objective is obtained within the variation range of independent variables, as shown in Figure 9. It shows that the hybrid algorithm of RBF and NSGA-II can effectively find the Pareto optimal solution set of the optimization problem under double optimization objectives. It is obvious from the figure that the objective functions $E_1$ and $E_2$ have the opposite trend, one of them increases while the other decreases. Now the maximum field strength of grounding shield is included in the optimization objective to form the three objective optimization problem. The same method is used to search the Pareto optimal solution, and the results are shown in Figure 9. Compared with the two-dimensional case, the three-dimensional Pareto optimal solution set is more complex, which constitutes continuous curve in three-dimensional space.
1) The results show that the maximum field strength of composite jacket of hollow insulator should be less than the control requirement of 0.9kV/mm; 2) the aluminum material used in the whole internal shielding system should be the least, that is, the volume of shielding cylinder $V$ should be as small as possible, and $V$ can be obtained by formula (19):

$$V = \sum_{i=1}^{2} \left[ \pi (R_i + d)^2 - \pi R_i^2 \right] L_i$$  \hspace{1cm} (19)

2) In equation (19), $D$ is the thickness of inner shielding aluminum cylinder, taking 3mm. According to the above two criteria, the Pareto optimal solution set is selected. Under the condition of double objective optimization, the minimum value of $V$ was $D_1 = 419.5086$mm, $D_2 = 845.2522$mm, $L_1 = 4311.6$mm, $L_2 = 1993.8$mm, $L = 550.4085$mm. Under the condition of three objective optimization, the minimum value of $V$ was $D_1 = 362.8136$mm, $D_2 = 790.401$mm, $L_1 = 4047.8$mm, $L_2 = 1688.6$mm, $L = 439.2188$mm. Three-dimensional finite element calculation is carried out under the two optimization schemes, and the maximum electric field intensity at each key position is listed in Table 4.

| Target value | $E_1$ | $E_2$ | $E_3$ | $E_4$ |
|--------------|------|------|------|------|
| Programme 1(V/mm) | 12625 | 9870 | 4980 | 830 |
| Programme 2(V/mm) | 12780 | 11755 | 5495 | 890 |

It can be seen from Table 4 that under the two optimized structural parameters, the maximum field strength at each key position of the through wall bushing can meet the control requirements, and the volume and maximum outer diameter of the internal shielding structure under scheme 2 are smaller than those under scheme 1. Therefore, the internal shielding structural parameters under scheme 2 are optimized for the trial production of UHV wall bushing prototype.

4. Conclusion

In this paper, the finite element method is used to simulate the three-dimensional electric field of the UHVDC through wall bushing, and the hybrid algorithm of RBF neural network and NSGA-II is realized. The algorithm is verified by the classical display function. Finally, the algorithm is applied to the optimization design of the shielding structure of the through wall bushing.

a) It is found that the high field strength is mainly concentrated on the inner shielding surface and the outer grading ring, and the wall and the grading ring near the wall have a good shielding effect on the surface field strength of the composite jacket.
b) In this paper, RBF neural network and NSGA-II algorithm are combined to solve multi-objective optimization problems, and the classical display function is used to verify the correctness of the algorithm. The results show that the algorithm can effectively achieve the multi-objective optimization problem, and the results of RBF network reconstruction are consistent with the original function optimization results, which provides a theoretical basis for the later use of RBF network instead of finite element calculation for multi-objective optimization.

c) The mathematical model of multi-objective optimization for the internal shielding of through wall bushing is established. Combined with RBF neural network and NSGA-II hybrid algorithm, the optimization design of the internal shielding structure is carried out. The optimization results make the field strength at each key position of the internal shielding meet the control requirements, and the materials used for the internal shielding structure are the least.

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