Efficient Electromagnetic Compatibility Optimization Design Based on the Stochastic Collocation Method

Xiaobing Niu, Shenglin Liu, and Runze Qiu

College of Marine Electrical Engineering
Dalian Maritime University, Dalian, 116026, China
emtf@dlmu.edu.cn, shaonian@dlmu.edu.cn, qiurunze321@163.com

***Abstract* –** Nowadays, in the field of electromagnetic compatibility (EMC), numerical methods such as finite element analysis are often used for simulation analysis. These numerical methods take a long time to solve some complex simulation problems, which is not conducive to the optimal design of EMC. In particular, the intelligent optimization algorithm that needs continuous iterative calculation will not be realized because of the long optimization time. This paper realizes the innovative application of the uncertainty analysis method (Stochastic Collocation Method) in EMC optimization design. Two typical EMC optimization design problems, namely, the prediction of cable crosstalk and the design of shielding performance of metal boxes, are proposed to verify the effectiveness of the optimization algorithm. Meanwhile, its performance is compared with the classical intelligent optimization algorithms such as genetic algorithms and immune algorithms.

***Index Terms* –** Efficient optimization design, electromagnetic compatibility, failure mechanism analysis, intelligent optimization algorithms, stochastic collocation method.

I. INTRODUCTION

Since the existence of the subject of Electromagnetic Compatibility (EMC), optimal design has been one of its important research contents. Due to the widespread randomness in the actual engineering environment, and the strong nonlinearity of the electromagnetic process, the optimization design of electromagnetic related performance is very difficult. In the 1990s, the International COMPUMAG Society presented the standard engineering problems, the Testing Electro-Magnetic Analysis Methods (TEAM), which are used to verify the correctness of electromagnetic field numerical analysis methods. Some of them involve optimization design about electromagnetic calculation, for example, TEAM 22 calculating example is the optimization design of superconducting magnetic energy storage systems, while TEAM 25 calculating example is the optimization design of magnetic field alignment die for anisotropic bonded permanent magnets [1, 2].

Around 2008 till now, intelligent optimization algorithms have been gradually introduced into EMC optimization design and achieved great success, such as particle swarm algorithm, genetic algorithm, immune algorithm and so on [3–6]. When the analytical method is used for forward prediction analysis or the single simulation time is short, intelligent optimization algorithms can get good optimization design results by virtue of their superior search ability. However, when the forward single simulation time is long, such as the complex EMC problem with finite element analysis method, intelligent optimization algorithms will lose competitiveness due to the long simulation time. Nowadays, with the requirements of multi-physical field coupling, uncertainty analysis and so on, the complexity of finite element analysis is increasing, which leads to the increase of various costs of EMC simulation prediction. At this time, intelligent optimization algorithms have no application.

Around 2014 till now, optimization algorithms based on surrogate model is becoming more and more popular in EMC simulation. The most representative methods are the Kriging model [7–9] and the surface response model based on radial basis function [10]. Their idea is to abstract the EMC prediction process into a substitute model, and then use intelligent optimization algorithms to optimize the agent model, so as to obtain the optimal design results. However, these methods have a fatal defect, that is, there is no accurate convergence judgment standard, which means the required EMC deterministic simulation times can only depend on the experience of the designers. When the number of EMC simulations is too low, the accuracy of optimal design is difficult to guarantee. When the number of EMC simulations is too high, it will cause a serious waste of computing resources.

Since 2013, uncertainty analysis is another hot research direction in the EMC field, and many methods have been successfully applied, such as the Monte Carlo

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Table 1: Comparison of performance of electromagnetic optimization algorithms

	Intelligent Optimization Algorithms	**Surrogate Models**	**SCM**
Efficiency calculation	Low	High	High
Convergence	Poor	Relatively Poor	Good
Global search capability	Strong	Weak	Relatively Strong
Suboptimal search capability	Weak	Relatively Strong	Strong

Method [11, 12], the Stochastic Reduced Order Models [13], and so on. There are many potential applications of uncertainty analysis methods, one of which is the worst-case estimation. Its implementation process is similar to the optimization process based on agent model. Unlike intelligent optimization algorithm, the optimization process based on uncertainty analysis method does not need iteration, so it has higher computational efficiency. Unlike the optimization process based on traditional agent model, uncertainty analysis has a strict convergence judgment method [14, 15], so its calculation efficiency and accuracy are guaranteed.

The Stochastic Collocation Method (SCM) is a non-embedded uncertainty analysis method, which has the characteristics of high calculation accuracy and high calculation efficiency, so it is very suitable for the application of optimum design [16–18]. Therefore, this paper selects it as an extended application of uncertainty analysis method in optimization design, and discusses its optimum performance in detail.

Table 1 compares the electromagnetic optimum performance of Intelligent optimization algorithms, Surrogate models and SCM, the SCM algorithm is shown to be more innovative.

The structure of the paper is as follows: Principle of the SCM applied to optimal design is presented in Section II. Section III gives the limitation of the SCM and its improvement scheme. Example of crosstalk prediction in the cable cascade model is shown in Section IV. Section V offers an example of shielding performance design of metal box. Prospect of the proposed optimization design method is discussed in Section VI. Section VII summarizes this paper.

II. APPLICATION OF THE SCM IN OPTIMIZATION PROCESS

For the uncertainty analysis methods, the inputs of the EMC simulation are regarded as random variables instead of deterministic constants. In optimization process, the parameters to be optimized also change within a certain range. If the range is treated as a random variable with uniform distribution, the optimization process can be equivalent to an uncertainty analysis problem. The one-to-one correspondence between the value range $[A_{\min}, A_{\max}]$ and the random variable ξ_i is shown as follows:

$$A(\xi_i) = \frac{A_{\max} + A_{\min}}{2} + \frac{A_{\max} - A_{\min}}{2} \times \xi_i. \tag{1}$$

Where ξ_i is the random variable obeying the uniform distribution in the range of $[-1, 1]$.

According to the generalized polynomial chaos theory, the SCM uses the Legendre polynomials to deal with uncertainty analysis problems with random variables of uniform distribution. The first terms of Legendre polynomials in one dimension are as follows:

$$\begin{cases} \varphi_0(\xi_i) = 1 \\ \varphi_1(\xi_i) = \sqrt{3}\xi_i \\ \varphi_2(\xi_i) = \frac{\sqrt{5}}{2}\left(3\xi_i^2 - 1\right) \\ \varphi_3(\xi_i) = \frac{\sqrt{7}}{2}\left(5\xi_i^3 - 3\xi_i\right). \end{cases} \tag{2}$$

The principle formula of the SCM is as follows:

$$\mathrm{EMC}_{\mathrm{SCM}}(\xi) = \sum_{j_1=1}^{m_1} \cdots \sum_{j_n=1}^{m_n} \mathrm{EMC}\left(a_{j_1}, \cdots, a_{j_n}\right) \mathrm{Lag}\left(a_{j_1}, \cdots, a_{j_n}\right). \tag{3}$$

Where $\left\{a_{j_1}, \cdots, a_{j_n}\right\}$ are collocation points, which are the tensor product of zero points of chaotic polynomials like formula (2). $\mathrm{EMC}\left(a_{j_1}, \cdots, a_{j_n}\right)$ means the EMC simulation result under the deterministic input parameters $\left\{a_{j_1}, \cdots, a_{j_n}\right\}$. $\mathrm{Lag}\left(a_{j_1}, \cdots, a_{j_n}\right)$ is the calculation results of Multi-dimensional Lagrange Interpolation on collocation points, and $\mathrm{EMC}_{\mathrm{SCM}}(\xi)$ is the final results in the form of random variable polynomials . Finally, the uncertainty analysis results are obtained by sampling random variable polynomials $\mathrm{EMC}_{\mathrm{SCM}}(\xi)$. The results can be the expected values, the standard deviation results, the probability density function results, the worst-case estimation results and so on.

According to the above theory, the core idea of the SCM is using the random variable polynomials to replace the EMC simulation process, and then the agent model $\mathrm{EMC}_{\mathrm{SCM}}(\xi)$ can be sampled to obtain the uncertainty analysis results. For the optimization problem, we can also build a similar agent model, and then use the exhaustive method to obtain the optimum results. As the SCM has excellent computational efficiency, the establishment of the agent model only requires several forward EMC simulations, and the number of simulations is the number of collocation points. Unlike the traditional intelligent optimization algorithm, which requires repeated iterations, the efficiency of the proposed optimization algorithm is obviously better.

In uncertainty analysis, how to judge the convergence of the algorithm is an important topic, and the Mean Equivalent Area Method (MEAM) is an effective method to solve this problem [14, 15]. Back to this paper, our question is how to judge the order of chaotic polynomials in the SCM. In reference [14], there is a clear solution for the SCM: By increasing the order of polynomials, the MEAM is used to quantitatively calculate the similarity between adjacent order uncertainty analysis results, and then determine the convergence order of the SCM. This similarity must be in the "Excellent" level, namely, the MEAM value is larger than 0.95 at this time.

It is worth noting that the explicit convergence judgment basis is the unique advantage of the uncertainty analysis method different from the traditional agent model optimum design method, which is an important guarantee for the accuracy of optimum design and calculation efficiency.

The following is a typical multi-peak functional problem to preliminarily verify the accuracy of the proposed algorithm. Our goal is to identify its maximum value:

$$f(x_1,x_2) = e - e^{\frac{\cos(2\pi x_1)+\cos(2\pi x_2)}{2}} + 2\pi - 2\pi e^{-0.2\times\frac{\sqrt{x_1^2+x_2^2}}{2}}. \tag{4}$$

The value range of parameter x_1 to be identified is the range [4,8], and that of parameter x_2 is the range [8,10].

Zero points of the 5-th order Legendre polynomials are applied, and the selection of the collocation points in the form of tensor product is completed as follows:

$$\{a_{j_1}, a_{j_2}\} = \{9.91, 9.54, 9.00, 8.46, 8.09\} \otimes \{7.81, 7.08, 6.00, 4.92, 4.19\}. \tag{5}$$

The result of parameter identification calculated by the SCM is $\{9.5453, 7.5097\}$. Substituting the result into formula (4), the maximum predicted value is 7.4980. The preliminary verification of the optimization effect is shown in Fig. 1. There are 3000 blue points, which are brought into formula (4) by the exhaustive method to verify the effect of parameter identification. The red star is the optimization result given by the SCM, which is obviously in the region where the optimal value is located.

Sorting 3000 sampling results, the results of the top 10 maximum values are shown in Table 2. Obviously, it verifies the effectiveness of the SCM in this optimization example. In this example, the SCM only needs to perform 25 times forward calculations of the formula (4). High computational efficiency of this proposed optimization algorithm is due to high convergence of the generalized polynomial chaos theory.

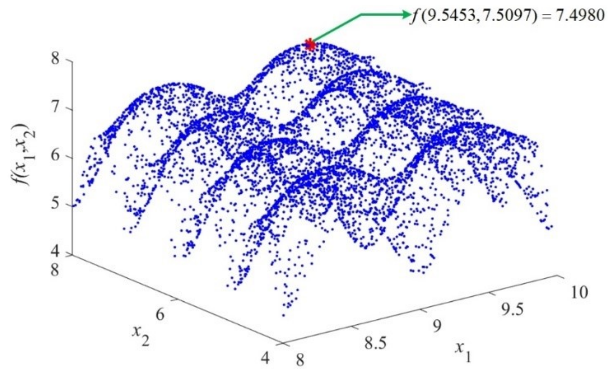

Fig. 1. Preliminary verification of the SCM in optimization effect.The red star is the maximum value position identified by SCM, and the blue dots represent the function value position of all grid points. It can be seen that the maximum value identified is consistent with the actual situation.

Table 2: Top 10 maximum values given by the exhaustive method

Order	Result
1	f(9.5073,7.5437)=7.4972
2	f(9.5589,7.5444)=7.4908
3	f(9.5463,7.4601)=7.4873
4	f(9.5975,7.5079)=7.4769
5	f(9.5975,7.5047)=7.4767
6	f(9.5534,7.5886)=7.4745
7	f(9.4821,7.4179)=7.4627
8	f(9.4154,7.5513)=7.4571
9	f(9.4169,7.5576)=7.4561
10	f(9.4466,7.4286)=7.4556

III. LIMITATION OF THE SCM AND ITS IMPROVEMENT SCHEME

In Section II, the effectiveness of the SCM in the optimization process has been preliminarily verified, especially its advantage of high computational efficiency.

However, choosing the collocation points in the form of tensor products will seriously affect the computational efficiency of the proposed optimization algorithm. The number of the collocation points is exponential with the number of random variables, which leads to the "curse of dimensionality". In this case, when there are many parameters to be identified, the times of the required forward simulations will increase explosively, and the SCM will lose its high computational efficiency. This is the limitation of the SCM, which suggests that the proposed optimization method is only applicable to a small number of parameters to be identified.

In uncertainty analysis, the sensitivity of different random variables can be predicted in advance in the pretreatment stage. The random variables with low sensitivity can be replaced by the mean values to achieve the purpose of dimension reduction. With dimensionality the help of this idea, this section puts forward the improvement scheme of the SCM into the optimization process.

Firstly, the sensitivity calculation formula is as follows, which is proposed in reference [19]. It is a numerical approximate calculation method based on Richardson extrapolation method under the difference scheme, and has good nonlinear processing ability:

$$\begin{aligned} S_i = 2 \times & \frac{y_{EMC}\left(\overline{\xi_1}, \cdots \overline{\xi_i} + \frac{\delta_i}{2} \cdots, \overline{\xi_n}\right)}{\frac{\delta_i}{2}} \\ & - 2 \times \frac{y_{EMC}\left(\overline{\xi_1}, \cdots \overline{\xi_i} \cdots, \overline{\xi_n}\right)}{\frac{\delta_i}{2}} \\ & - \frac{y_{EMC}\left(\overline{\xi_1}, \cdots \overline{\xi_i} + \delta_i \cdots, \overline{\xi_n}\right)}{\delta_i} \\ & - \frac{y_{EMC}\left(\overline{\xi_1} \cdots \overline{\xi_i} \cdots, \overline{\xi_n}\right)}{\delta_i}, \end{aligned} \tag{6}$$

where $\overline{\xi_i}$ is the mean value of the random variable ξ_i, $y_{EMC}()$ indicates forward EMC simulation at the specific collocation point. δ_i is a small perturbation, and its value can be assumed to be $\frac{\max(\xi_i) - \min(\xi_i)}{2}$.

The improvement scheme of the SCM in the optimization process is as follows, and it divides the sensitivity into different levels before SCM calculation.

Step 1, according to formula (1), all parameters to be identified are transformed into random variables obeying the uniform distribution.

Step 2, according to formula (6), the sensitivity of every random variable is calculated, and it is used to classify random variables.

Step 3, random variables with low sensitivity are replaced by their mean values, and the SCM is used to carry out the optimization process on high sensitive random variables.

Step 4, random variables with high sensitivity are replaced by their optimal values calculated in the Step 3, and the SCM is used to carry out the optimization process a second time on low sensitivity random variables.

Step 5, the final results are the combination of all optimization parameters in the Step 3 and the Step 4.

Obviously, in this improvement scheme, the SCM optimizations are carried out twice for high sensitivity parameters and low sensitivity parameters respectively, so as to achieve the purpose of mitigating the "curse of dimensionality". For example, suppose that the number of parameters to be optimized is six, and the number of forward EMC simulations required for the normal SCM optimization is $5^6 = 15625$. Using the improvement scheme, this number is reduced to $2 \times 5^3 = 250$. In the process of sensitivity calculation, some forward EMC simulation times are added. Each random variable corresponds to the simulation of two perturbation quantities δ_i and $\frac{\delta_i}{2}$, plus the simulation at the mean value $\left(\overline{\xi_1}, \cdots \overline{\xi_i} \cdots \overline{\xi_n}\right)$, so the number of increases times is thirteen. The number of forward EMC simulations required for the improvement scheme is 263.

It is worth noting that the sensitivity of random variables can be divided into several levels, not just high level and low level, in order to improve the computational efficiency of the optimization process.

To sum up, the improvement scheme can effectively avoid the impact of the "curse of dimensionality" limitation of the SCM on the calculated efficiency of the optimization algorithm, which broadens the scope of application of the optimization algorithm proposed in this paper.

IV. EXAMPLE OF CROSSTALK PREDICTION IN THE CABLE CASCADE MODEL

In order to describe the geometric randomness caused by bundling or other factors, the cascaded transmission line model is usually used to model the cables [17]. According to the electromagnetic field theory, the closer the distance between cables, the stronger the electromagnetic coupling effect, and the greater the crosstalk between lines. According to this theorem, an optimization problem with known optimization results can be constructed through a cascade model, in order to verify the effectiveness of the proposed algorithm in this paper.

The schematic diagram of the cable cascade model is shown in Fig. 2. Two cables are laid flat on the ground aluminum plate, which are cascaded by six uniform transmission line models. The pink line is an interference emission line with a diameter of 0.07 m. The green line is the interference receiving line with a diameter of 0.09 m. According to the coordinate axis direction in Fig. 2, in

Fig. 2. Schematic diagram of the cable cascade model. The pink cable has electromagnetic interference, while the green one is the disturbed cable.

this example, the geometric position of the cable can be changed only in the x-axis direction.

Figure 3 shows the circuit schematic diagram of the crosstalk prediction problem. Both cables are 1m long and all load impedances are 50 Ω. The electromagnetic interference source is a sinusoidal excitation source with the amplitude of 1V and the frequency of 40 MHz. $U_{\text{crosstalk}}$ refers to the voltage crosstalk amplitude at the load end of the interference receiving line. The forward EMC simulation solver is the Finite Difference Time Domain method. The electrical parameters in the transmission line model are given by the image method and the electric axis method. Obviously, the ground heights of the two cables are their radius, namely 0.045 m and 0.035 m. Assume that the x-axis coordinates of the six transmission lines of the interference emission line are fixed, which are $\{2.5$ m, 5.5 m, 5.7 m, 8.2 m, 6.9 m, 2.8 m$\}$. The x-axis coordinates of the six transmission lines of the interference receiving line are parameters to be optimized. The optimization objective is to maximize the crosstalk value $U_{\text{crosstalk}}$. More information about crosstalk calculation is consistent with reference [17].

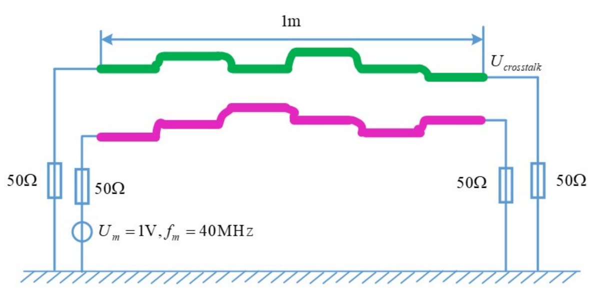

Fig. 3. Schematic diagram of the cable cascade model. The pink cable has electromagnetic interference, while the green one is the disturbed cable.

The value range of parameters to be optimized is from 1 m to 10 m. Obviously, the answer to this optimization problem is known. That is, when the two cables coincide, the crosstalk value is the largest, so the answer to the optimal design is $\{2.5$ m, 5.5 m, 5.7 m, 8.2 m, 6.9 m, 2.8 m$\}$. At this time, the crosstalk value is 0.0163 V. Since the cables in the example are solid (with radius), they cannot be completely coincident. Therefore, when calculating the distance between cables in the image method, when it is less than the sum of the radius of two cables $0.045 + 0.035 = 0.08$ m, the distance is directly equal to 0.08 m.

This article primarily aims to identify the optimal value of the simulation model, which is independent of the actual test results; therefore, no corresponding test results are provided.

Using the improved optimization algorithm mentioned in Section III, the optimization result is $\{2.5869$ m, 5.5014 m, 5.6186 m, 8.0243 m, 7.4948 m, 2.7990 m$\}$. The crosstalk value under this result is 0.0056 V.

The genetic algorithm and the immune algorithm are compared to verify the performance of the proposed algorithm. In the immune algorithm, 40 chromosome individuals are used for three generations of evolution, and the total number of forward EMC simulations required is 883. The final optimization result of the immune algorithm is $\{9.4595$ m, 3.8242 m, 5.6702 m, 8.2771 m, 6.9049 m, 2.7770 m$\}$, and its crosstalk value is 0.0037 V. The number of forward EMC simulation required by the SCM is only 263, less than one-third of 883, but its optimization result is better than that of the immune algorithm.

For the genetic algorithm, 60 chromosomes are used for 20 iterations, and the results are shown in Table 3. The final identification result of the SCM is better than that of the first 14 generations of the genetic algorithm. Similarly, the number of forward EMC simulations required is less than one-third of that of the genetic algorithm.

The intelligent optimization algorithm needs to obtain the optimal solution through repeated iterative evolution, while the SCM only completes

Table 3: Optimization results of genetic algorithm in crosstalk prediction example

Iteration Times	Simulation Times	Crosstalk Value
1	120	0.0011V
2	180	0.0011V
3	240	0.0017V
4	300	0.0017V
5	360	0.0023V
6	420	0.0023V
7	480	0.0024V
8	540	0.0032V
9	600	0.0032V
10	660	0.0032V
11	720	0.0033V
12	780	0.0034V
13	840	0.0040V
14	900	0.0049V
15	960	0.0059V
16	1020	0.0062V
17	1080	0.0063V
18	1140	0.0063V
19	1200	0.0063V
20	1260	0.0063V

the identification through a single operation without an iterative process. Therefore, the SCM can quickly obtain the local optimal solution because of its high convergence, but its ability to obtain the global optimal solution is obviously inferior to the intelligent optimization algorithm. Table 3 shows the ability of the genetic algorithm to seek the global optimal solution in the process of continuous iteration. It means that the SCM is more suitable for optimization problems where a single forward EMC simulation takes too long. The reason is that the intelligent optimization algorithm cannot be used because of its low computational efficiency. When the single EMC simulation time is short, the intelligent optimization algorithm is still the first choice.

V. EXAMPLE OF SHIELDING PERFORMANCE DESIGN OF METAL BOX

In order to verify the practicability of the proposed algorithm, this chapter applies it to the electromagnetic protection design example of metal box, and its design details are shown in Fig. 4. The size of the anechoic chamber is $3.9 \times 3.9 \times 3.3\text{m}^3$. The shielding material is carbon-loaded foam with low conductivity. There is a biconical antenna at the center of the darkroom, and this position is also assumed to be the coordinate origin. The details of the coordinate axis are also shown on the right side of Fig. 4. The antenna emits the spherical wave at the frequency of 10 MHz, other settings of the model are consistent with those shown in reference [20].

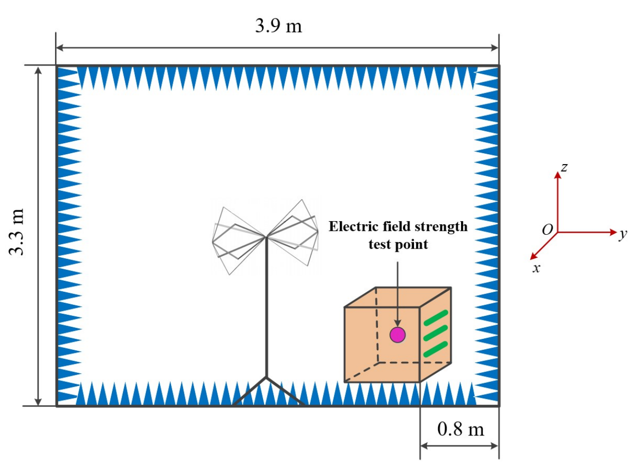

Fig. 4. Schematic diagram of shielding performance design. The green lines represent the strip cooling holes, which are supposed to be facing away from the antenna to achieve the best electromagnetic shielding effect.

There is an aluminum box 0.8 m away from the right wall of the anechoic chamber, and this position is fixed. The size of the box is $0.6 \times 0.6 \times 0.6\text{m}^3$ with a thickness of 0.02 m. There is an electromagnetic-sensitive device in the middle of the aluminum box. Therefore, the electric field strength at this location needs to be predicted, and the value should be minimized in the design process.

Similarly, there are six parameters to be optimized in this example. The first two parameters are the position parameters of the aluminum box in the x-axis and z-axis directions. Take the center point (pink test point) of the aluminum box in Fig. 4 as the reference point, and the value ranges of their coordinates are both $[-0.8\text{ m}, 0.8\text{ m}]$.

There are three cooling holes on the right side of the metal box, and its enlarged view is shown in Fig. 5. The lengths of the three holes are the parameters to be identified, and their value ranges are [0.36 m,0.44 m]. The width of the holes is assumed to be 0.01 m. The last parameter to be identified is the distance between the hole at both ends and the hole in the middle. It is assumed that the distance between the center and both ends is the same, that is, $h_1 = h_2$. Its value range is [0.06 m, 0.1 m]. Similarly, this example exclusively presents the optimization results derived from the simulation model.

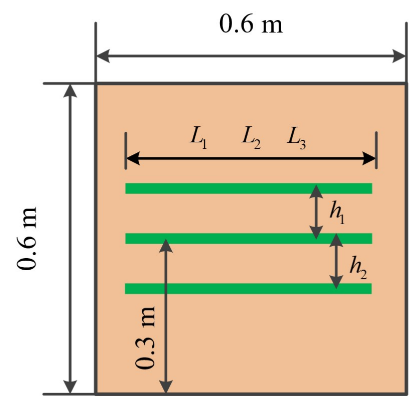

Fig. 5. Enlarged view of position information of cooling holes in the aluminum box. The length and relative position of the cooling holes are parameters to be optimized.

Using the optimization algorithm proposed in Section III, third order Legendre polynomials are selected, so the number of forward EMC simulations is $2 \times 3^3 + 2 \times 6 + 1 = 67$. The determination method of the order will be discussed in the next section. The final optimization result of the SCM is {-0.7991 m, 0.5456 m, 0.3970 m, 0.3600 m, 0.3609 m, 0.0609 m}, and the electric field strength value at this time is 3.0765×10^{-5} V/ m.

Table 4 shows the comparative optimization results of the genetic algorithm. A total of 60 chromosomes are used for 10 iterations. The SCM identification result is better than the results of the first two generations. In this case, the number of forward EMC simulations

Table 4: Optimization results of genetic algorithm in crosstalk prediction example

Iteration Times	Simulation Times	Crosstalk Value
1	120	3.5658×10^{-5} V/m
2	180	3.3418×10^{-5} V/m
3	240	2.4779×10^{-5} V/m
4	300	2.4779×10^{-5} V/m
5	360	2.4779×10^{-5} V/m
6	420	2.4779×10^{-5} V/m
7	480	2.4779×10^{-5} V/m
8	540	2.4779×10^{-5} V/m
9	600	2.4779×10^{-5} V/m
10	660	2.4779×10^{-5} V/m

required in the SCM is less than one-third of that of the genetic algorithm. However, after three generations of iteration, the genetic algorithm can quickly identify the global optimal solution. Therefore, the conclusion obtained through comparison is consistent with that in Section IV, that is, the SCM is better at finding the suboptimal solution quickly, while the genetic algorithm is inefficient but can find the global optimal solution.

It is worth noting that the genetic algorithm has converged in the third generation, but it cannot be determined that it has converged until the tenth generation. Therefore, in the practical application, the optimization design method based on the SCM has greater advantages in computational efficiency.

In order to further demonstrate the accuracy of the SCM, the optimization results of the exhaustive method are proposed for comparison. Sorting 500 sampling results, the optimization results of the top five minimum electric field strength values are shown in Table 5. Obviously, the optimization result given by the SCM is better than 500 sampling results in the exhaustive method. This is enough to prove the accuracy of the SCM in the optimization process.

Table 5: Optimization results of genetic algorithm in crosstalk prediction example

Order	Parameters [m]	Electric Field Intensity
1	−0.7991, −0.3189, 0.3757, 0.3908, 0.4276, 0.0888	3.3811×10^{-5} V/m
2	0.7845, −0.2846, 0.3799, 0.3733, 0.3796, 0.0972	3.4548×10^{-5} V/m
3	0.7131, −0.0191, 0.3720, 0.4344, 0.3800, 0.0964	3.5168×10^{-5} V/m
4	0.7946, 0.5739, 0.4131, 0.3665, 0.3848, 0.0743	3.5791×10^{-5} V/m
5	0.6650, 0.5878, 0.4023, 0.4335, 0.4123, 0.0958	3.5996×10^{-5} V/m

VI. PROSPECT OF THE PROPOSED OPTIMIZATION DESIGN METHOD

Prospect 1: Relationship between the number of sensitivity categories and the performance of optimization algorithm.

In this paper, sensitivity is only divided into high level and low level, but it can be divided into many categories. In the future work, especially in the multi-parameter optimization design problem, how to select the number of levels scientifically and reasonably will be discussed. Among them, the relationship between the number of the levels and the accuracy of the SCM, and how to allocate this number to maximize the calculation efficiency of the SCM are both worth discussing.

Prospect 2: Application of the proposed optimization algorithm in robust optimal design.

Due to the existence of manufacturing error and randomness in the actual engineering environment, the sub-optimal solution with low sensitivity is sometimes more practical than the optimal solution with high sensitivity. Therefore, the concept of robust optimal design has been proposed in recent years [21, 22]. The optimization algorithm proposed in this paper can quickly find the suboptimal solution, so it is expected to be well applied in robust optimization design, especially in some cases where online identification is required.

VII. CONCLUSION

In this paper, the SCM, which is originally an uncertainty analysis method, is creatively applied to EMC optimization design to solve low computational efficiency problems of traditional intelligent optimization algorithms when single forward simulation takes a long time. Combined with the sensitivity approximate calculation method based on the Richardson extrapolation, an improved optimization scheme considering multiple sensitivity levels is proposed to avoid the adverse impact of the “curse of dimensionality” problem of the SCM with the optimum performance. Based on professional background of the EMC, two typical examples are designed. They are crosstalk prediction of cable cascade model and shielding performance design of metal box. The optimal design results of the SCM are quantitatively compared with those of genetic algorithm and immune algorithm, and the following conclusions are drawn. The SCM can quickly find the sub optimal solution or locally optimal solution. On the premise that it can only carry out finite forward simulations, the optimum performance of the SCM is better than that of the intelligent optimization algorithm. However, the search ability of the SCM is not as good as that of intelligent optimization algorithm, so when the time of single forward simulation is short or the cost of single simulation is small, intelligent optimization algorithm is still a better choice.

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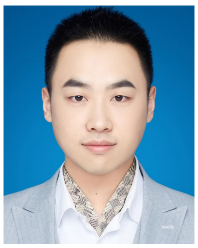
Xiaobing Niu received the B.S. degree in electrical engineering and the M.E. degree in electrical drive and its automation from Dalian Maritime University, Dalian, China, in 1991 and 1998, respectively. He is currently an Associate Professor with the School of Marine Electrical Engineering, Dalian Maritime University. His current research interests include motor control theory and its applications, energy transformation and its EMC problem.



Shenglin Liu received the B.S. degree in marine electronic and electrical engineering from Dalian Maritime University, Dalian, China, in 2015. He is currently working toward the M.E. degree in Dalian Maritime University. His current research interests include modular multilevel converters control theory with applications to high voltage direct current and design of power electronic interfaces.

Runze Qiu received the B.S. degree in electrical engineering and automation from Hohai University, Nanjing, China, in 2022.He is currently pursuing the master's degree in electrical engineering at Dalian Maritime University, Dalian, China.His current research interests include modular multilevel converters in marine electrical systems, and transmission systems for offshore wind power.