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Uncertainty Analysis Method for Electromagnetic Compatibility Simulation Based on Random Variable Black Box Model

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ABSTRACT: In recent years, uncertainty analysis is a hot topic in the field of electromagnetic compatibility simulation. The actual electromagnetic environment is simulated by considering the randomness of the model input parameters. However, there are currently two key issues that have not been resolved. One is the curse of dimensionality problem that occurs when there are many random variables. The other is how to establish a random input model with generality and portability. In order to address these issues, this paper proposes a new random input modeling method called random variable black box model. When applying to the Stochastic Collocation Method with dimensionality reduction sparse grid strategy, the applicability of this uncertainty analysis method can be extended to any probability density function, then enabling efficient electromagnetic compatibility simulation uncertainty analysis of high-dimensional random variable models and fundamentally solving the curse of dimensionality problem. Finally, this paper implements a joint simulation technology of the MATLAB software and COMSOL software to verify the strong portability of the random variable black box model, ensuring that advanced uncertainty analysis methods can be smoothly introduced into commercial electromagnetic simulation software and expanding the application scope of uncertainty analysis.

1. INTRODUCTION

Uncertainty analysis is a hot research topic in the field of Electromagnetic Compatibility (EMC) in recent years. It can improve the reliability and practicality of EMC simulation models or methods, by treating numerical simulation input parameters as uncertain parameters, such as random variable models, random fuzzy variable models, and fractal dimension models. Usually, the uncertainty of simulation input is caused by factors such as actual environmental motion or vibration, manufacturing tolerances, loose connections, and cognitive deficiencies of researchers.

Monte Carlo Method (MCM) is the most commonly used uncertainty analysis method, which is based on the weak law of large numbers. The randomness of simulation inputs is described through a large number of discrete sampling points [1]. All possible scenarios are considered by the MCM; therefore, MCM is most in line with researchers' understanding of uncertainty concept. Therefore, MCM is suitable as a standard to verify the accuracy of other uncertainty analysis methods in theoretical research, rather than using actual measurement data. Although MCM has the advantages of high computational accuracy and easy implementation, it also has the problem of low computational efficiency caused by poor convergence, making it not competitive in practical engineering applications [2].

Subsequently, some efficient uncertainty analysis methods (such as traceless transformation method [3], perturbation method [4, 5], method of moment [6], and direct solution method [7]) are gradually applied in the EMC field, but they all have varying degrees of computational accuracy issues. Especially when faced with electromagnetic simulation considering resonant frequency, high nonlinearity makes that small changes in input parameters will cause drastic changes in output parameters. At this time, these numerical approximation methods will generate truncation errors, such as the Taylor formula expansion of the method of moment or the perturbation polynomial expansion of the perturbation method.

In 2013, the generalized polynomial chaos theory was introduced into EMC simulation by the Turin Institute of Technology research team in Italy. Multiple typical uncertainty analysis problems have been solved, such as bundled cable crosstalk analysis, random interference source field line coupling analysis, and Printed Circuit Board (PCB) wiring electromagnetic coupling analysis [8–11]. This theory includes two numerical solution methods, namely the Stochastic Galerkin Method (SGM) and Stochastic Collocation Method (SCM), both of which have the dual advantages of high computational accuracy and efficiency. SGM is an embedded uncertainty analysis method, although it has slightly higher accuracy than SCM, and it cannot as applicable as the SCM. SCM is a non-embedded uncertainty analysis method which requires only a stable solver, and it has the same applicability as MCM.

However, for SGM and SCM, the curse of dimensionality is a big factor affecting their performance. When the number of random variables describing uncertain inputs increases, the

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number of chaotic polynomials in SGM and the number of collocation points in SCM both exponentially increase, leading to a sharp decrease in computational efficiency, which is known as the curse of dimensionality problem. Some literature points out that when the number of random variables exceeds 20, the computational efficiency of SGM, SCM, and MCM is almost the same [12, 13]. With the deepening of research, more and more uncertainty analysis methods are found to be plagued by the curse of dimensionality. Therefore, how to respond to this challenge has become a hot research topic in the past five years.

In response to the curse of dimensionality, the hierarchical dimensionality reduction method of chaotic polynomials is proposed in [12], and its mathematical theoretical derivation is reasonable. However, in practical applications, the truncation error of each layer will gradually accumulate in the transmission of each layer, ultimately affecting the accuracy of the simulation. The basis function of high-dimensional random variables based on tensor method is constructed in [13] to improve the computational efficiency of sparse solvers. However, when the nonlinearity of EMC simulation is high, good uncertainty description ability is difficult to maintain by the solvers, which affects computational accuracy. A polynomial meta model with standardized low rank approximation is constructed by [14] and [15] to reduce the dimensionality of random variables, but its accuracy is only applicable to cases where the EMC model is simple (with small nonlinearity and small input output range). Stochastic Reduced Order Models (SROM) method is proposed in [16], but its convergence is difficult to effectively determine in practical applications. When the number of selected representative sampling points is small, its accuracy cannot be guaranteed. And when the number of representative sampling points is large, there is still a problem of curse of dimensionality. The improved method of moment (IMOM) based on Richardson's extrapolation method is proposed in [17], but its accuracy in calculating the mean is still poor, which affects the accuracy of the overall uncertainty analysis results. The Dimension-Reduced Sparse Grid Strategy for the SCM (DRSG-SCM) proposed in [18] can effectively solve the problem of curse of dimensionality, but its applicability is limited by the probability density function of input random variables (the probability density function is symmetric about the y-axis), such as the uniformly distributed random variables and Gaussian distributed random variables. In summary, there is currently no uncertainty analysis method that can completely solve the curse of dimensionality problems.

In addition, in early research, researchers focused more on the quantitative transmission process of uncertainty from input to output, but to some extent ignored the importance of uncertainty input modeling for simulation results. Therefore, in addition to the random variable models, random fuzzy variable models [19], fractal dimension models [20], and random process models [21] are gradually introduced into the EMC field to improve the accuracy of uncertainty description. However, for users, these high-end random input models are not easy to understand, and the modeling process is difficult to implement. Especially when commercial simulation software for models is applied, incorrect understanding of uncertainty input can easily lead to confusion between uncertainty and error concepts, and instead reduce the credibility of the input model.

In order to better handle uncertainty, the Random Variable Black Box Model (RVBBM) is proposed in this paper to achieve modeling of EMC simulation inputs. Compared to other complex and difficult to understand modeling methods, RVBBM is more intuitive and avoids confusion between researchers and users about the concept of uncertainty. At the same time, RVBBM and DRSG-SCM are effectively combined to solve the curse of dimensionality problem faced in high-dimensional random variable spaces, ultimately achieving the promotion of new uncertainty analysis methods in commercial electromagnetic simulation software.

The structure of this article is as follows. Section 2 provides a detailed introduction to the principles of RVBBM. Section 3 verifies the calculation accuracy of RVBBM. Section 4 combines RVBBM and DRSG-SCM to achieve efficient uncertainty analysis. In Section 5, a parallel cables crosstalk prediction example is used to verify the effectiveness of the proposed uncertainty analysis method. In Section 6, the promotion of the RVBBM in the commercial electromagnetic simulation software COMSOL is implemented, and the uncertainty analysis of the shielding effectiveness calculation example of the metal box is achieved based on DRSG-SCM. Section 7 explores the future research directions of RVBBM. Section 8 summarizes the entire text.

2. PRINCIPLE OF RANDOM VARIABLE BLACK BOX MODEL

In the process of modeling the uncertainty of simulation input parameters, uncertainty and error are two concepts that are easily confused. Error refers to the deviation caused by inaccurate models or algorithms when actual electromagnetic phenomena are simulated, while uncertainty refers to the inherent changes in simulation input parameters. Both can lead to uncertainty in simulation results, but their sources are completely different.

The essence of uncertainty modeling is to consider all possible scenarios, which is also the mathematical mechanism of MCM. The uncertainty of input parameters comes from the movement or vibration of the actual environment, tolerances in the manufacturing process, loose connections, cognitive deficiencies of researchers, etc. Therefore, simulation results should cover the impact of all possible scenarios, and uncertainty analysis methods should be used to quantitatively evaluate the transmission process.

The RVBBM proposed in this article is a modeling method that approximates all possible scenarios, and its core idea is consistent with [12]. In [12], intermediate variables are constructed by researchers to achieve orthogonalization of chaotic polynomials. However, RVBBM advances by retreating, constructing input variables that can generate specific possible scenarios based on numerical approximation methods, and assisting in the efficient implementation of subsequent uncertainty analysis methods by freely adjusting the properties of random variables.

The modeling process of the RVBBM is as follows:

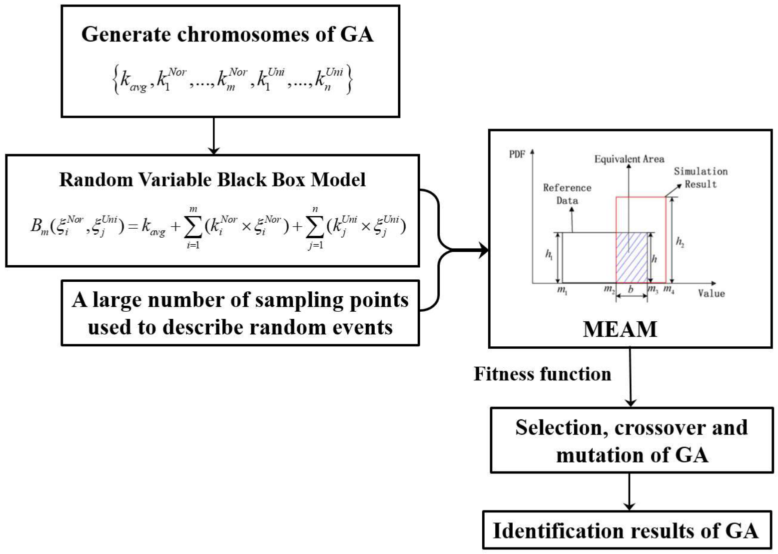

FIGURE 1. Flow chart of RVBBM parameter identification based on the GA.

$$B_m(\xi_i^{Nor}, \xi_j^{Uni}) = k_{avg} + \sum_{i=1}^{m}(k_i^{Nor} \times \xi_i^{Nor}) + \sum_{j=1}^{n}(k_j^{Uni} \times \xi_j^{Uni}) \tag{1}$$

Among them, ξ_i^{Nor} is a normally distributed random variable, and ξ_j^{Uni} is a uniformly distributed random variable within the range of $[-1, 1]$. k_{avg}, k_i^{Nor}, and k_j^{Uni} are the parameters to be identified. In addition, the number of random variables, namely m and n, needs to be determined. The purpose of choosing uniform distribution and normal distribution here is because they have good traversability, and the probability density curve is symmetric about the y-axis, which is not limited by DRSG-SCM method.

The theoretical basis of RVBBM is Bayesian Neural Network (BNN) model. In BNN model, the input of the model is a random variable, which enables the transmission of uncertainty in the neural network model to enhance the robustness and generalization ability of the algorithm [22–24]. Therefore, RVBBM can be regarded as a single-layer BNN equivalent model with strong uncertainty description ability.

To determine the parameters to be solved in RVBBM, an optimization algorithm needs to be introduced. Due to the low complexity of the RVBBM parameter identification optimization problem, almost all intelligent optimization algorithms can complete this task, and the most commonly used Genetic Algorithm (GA) is chosen in this paper [25–27]. The difficulty of the optimization process is how to accurately and quantitatively evaluate the difference between the uncertainty of actual random factors and the uncertainty described by RVBBM, and then determine the fitness function in the GA. The Mean Equivalent Area Method (MEAM) is a method for evaluating the effectiveness of uncertainty analysis results based on the characteristics of the EMC simulation. When the standard data (usually the uncertainty analysis results of the MCM) is known, the difference between the evaluated results and the standard data is quantitatively calculated to determine the effectiveness of the uncertainty analysis method to be evaluated. MEAM is used in this article to provide the fitness function of the GA, and more details about MEAM can be found in [28] and [29].

The process of identifying the RVBBM parameters based on the GA is shown in Figure 1, and the specific steps are as follows:

(1) The RVBBM parameter $\{k_{avg}, k_1^{Nor}, \ldots, k_m^{Nor}, k_1^{Uni}, \ldots, k_n^{Uni}\}$ to be identified is considered as the chromosome of the GA.
(2) For each chromosome, random variables ξ_i^{Nor} and ξ_j^{Uni} are sampled, and the probability density function corresponding to each chromosome is generated.
(3) For a large number of sampling points that can describe random events, a probability density function is also generated and recognized as standard data.
(4) Based on MEAM, the difference between the two probability density functions is quantitatively calculated, and the fitness function value for each chromosome is determined.
(5) The selection, crossover, and mutation operations of genetic algorithms are performed to seek the optimal solution.
(6) The final identification results are obtained, and the construction of RVBBM is completed.

From this, it can be seen that the concept of RVBBM is clear, which not only simplifies the uncertainty input modeling process, but also effectively avoids the confusion between uncertainty and error, which is beneficial for researchers in the EMC field to use uncertainty analysis methods more accurately.

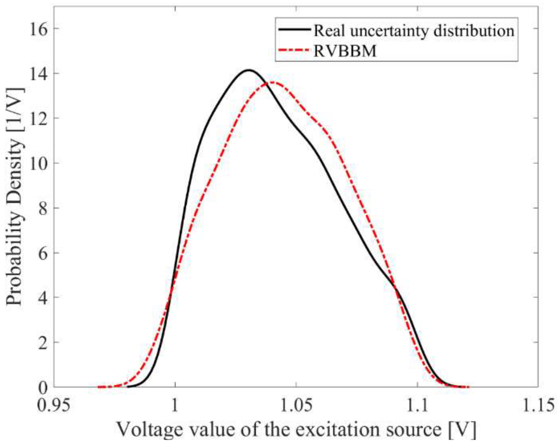

FIGURE 2. Probability density curves of voltage parameter calculation example.

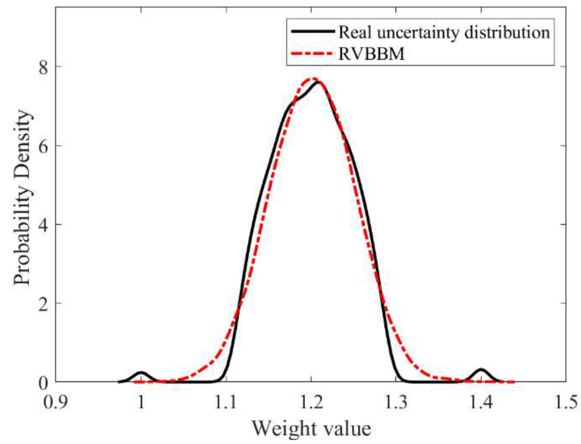

FIGURE 3. Probability density curves of weight parameter calculation example.

3. VERIFICATION OF RVBBM CALCULATION ACCURACY

The accuracy of the RVBBM modeling process is verified in this section through examples of voltage parameters and weight parameters.

3.1. Example of Voltage Parameter Calculation

The first uncertainty model that RVBBM needs to construct is the voltage value of a certain excitation source E_m, which is expressed as follows:

$$E_m(\xi_x) = 1 + 0.1 \times \xi_x \text{ [V]} \tag{2}$$

Assume that the Probability Density Function (pdf) of its actual uncertainty distribution is:

$$pdf(\xi_x) = \begin{cases} \frac{1}{2}\sin\left(\frac{3\pi}{2}\xi_x\right) + \left(1 - \frac{1}{3\pi}\right), & 0 \le \xi_x \le 1 \\ 0, & \xi_x \text{ represents other values} \end{cases} \tag{3}$$

The probability density distribution can be obtained through direct measurement or theoretical derivation and estimation, usually in the form of a large number of sampling points under real engineering conditions. In this article, in order to verify the accuracy of RVBBM, it is assumed that its true situation is described by formula (3). According to calculations, the integration result of $pdf(\xi_x)$ in the range of negative infinity to positive infinity is equal to 1, and $pdf(\xi_x) \ge 0$, so it satisfies all the conditions of the probability density curve.

The modeling results of RVBBM are as follows:

$$E_m^{RVBBM} = 1.045 + 0.020 \times \xi_1 + 0.038 \times \xi_2 \text{ [V]} \tag{4}$$

Among them, ξ_1 and ξ_2 are uniformly distributed random variables within the interval $[-1,1]$. The comparison between the true uncertainty distribution given by formula (3) and the probability density curve of the model constructed by RVBBM is shown in Figure 2. The common area of the two probability density curves in Figure 2 is 97.36%, greater than 95%, which belongs to the "excellent" level [28]. The accuracy of the RVBBM in voltage parameter modeling is verified.

3.2. Example of Weight Parameter Calculation

The second uncertainty model that RVBBM needs to construct is a certain weight parameter $W_m(\xi_y)$, whose expression is as follows:

$$W_m(\xi_y) = 1{+}0.1 \times \xi_y \tag{5}$$

Assume that the probability density function of its true uncertainty distribution is:

$$pdf(\xi_y) = \begin{cases} \frac{3}{8}\left[-2\xi_y^2 + 8\xi_y - 6\right], & 1 \le \xi_y \le 3 \\ 0, & \xi_y \text{ represents other values} \end{cases} \tag{6}$$

Obviously, $pdf(\xi_y)$ also satisfies the conditions of the probability density curve.

The modeling results of RVBBM are as follows:

$$W_m^{RVBBM} = 1.202 + 0.051 \times \xi_3 \tag{7}$$

Among them, ξ_3 is a normally distributed random variable. Figure 3 shows the probability density curve comparison results of the weight parameter calculation example, with a common area of 97.92%, which also verifies the accuracy of RVBBM.

4. UNCERTAINTY ANALYSIS METHOD BASED ON RVBBM AND DRSG-SCM

SCM is a nonembedded uncertainty analysis method based on generalized polynomial chaos theory. Deterministic EMC simulations are conducted at selected collocation points, and uncertainty analysis results are obtained through multidimensional Lagrange interpolation. It has the advantages of high computational accuracy, high computational efficiency, and wide applicability. However, the tensor product form is adopted by the traditional SCM to select collocation points, which inevitably leads to the problem of curse of dimensionality.

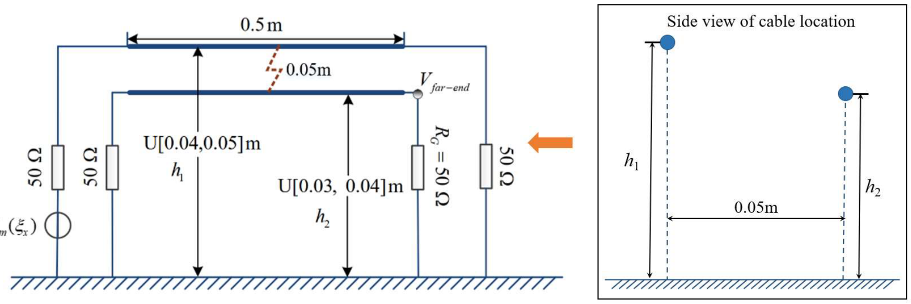

FIGURE 4. Crosstalk prediction example for parallel cables in References [29] and [30].

DRSG-SCM is an improved algorithm of SCM, which greatly reduces the number of required collocation points through a dimensionality reduction sparse grid strategy. DRSG-SCM has a two-layer collocation points structure: (1) the first layer only has $u_1 = \{0\}$, which is the zero point of the first-order chaotic polynomial (2). The second layer contains $M = 2k + 1$ collocation points, such as $u_2 = \{0, \pm A_1, \pm A_2, \ldots, A_k\}$, which are the zeros of other odd order chaotic polynomials [18]. Therefore, if the dimensionality reduction sparse grid strategy is to be used, the probability density function of the random variables must be symmetric about the y-axis, such as the uniform distribution or normal distribution of the interval $[-1,\ 1]$; otherwise, the symmetry of the two-layer collocation points cannot be guaranteed, which is the limitation of DRSG-SCM.

The principal formula of DRSG-SCM is as follows:

$$E\tilde{M}C_{\text{DRSG}}(\xi) = A_1(n+1, n) + \sum_{m=1}^{n} A_{2,m}(n+1, n) \quad (8)$$

Among them, $E\tilde{M}C_{\text{DRSG}}(\xi)$ is the multidimensional Lagrange interpolation result under the dimensionality reduction sparse grid strategy. The number of random variables is n, and $A_1(n+1, n)$ and $A_{2,m}(n+1, n)$ are the collocation points selected by DRSG-SCM.

$$A_1(n+1, n) = -(n-1) \times \left(\underbrace{\text{EMC}_u^1 \otimes \cdots \otimes \text{EMC}_u^1}_{n} \right) \quad (9)$$

$$A_{2,m}(n+1, n) = \underbrace{\text{EMC}_u^1 \otimes \cdots \otimes \text{EMC}_u^1}_{m-1} \otimes \text{EMC}_u^2 \otimes \underbrace{\text{EMC}_u^1 \otimes \cdots \otimes \text{EMC}_u^1}_{n-m} \quad (10)$$

The total number of collocation points required for the DRSG-SCM is:

$$T_n = 1 + (M-1) \times n \quad (11)$$

Obviously, there is a linear relationship between the total number of collocation points T_n and the random variable n, which is the most important property of the DRSG-SCM.

A large number of sampling points can be used for uncertainty modeling by RVBBM, indicating that RVBBM has excellent applicability. According to principal formula (1), its model is a linear combination of a uniform distribution with an interval of $[-1,1]$ and a standard normal distribution, which can effectively solve the limitation of the DRSG-SCM's dimensionality reduction sparse grid strategy on the condition that the probability density function must be symmetric about the y-axis. That is, the combination of RVBBM and DRSG-SCM can completely solve the curse of dimensionality problem of uncertainty analysis.

It is worth noting that although there is a probability of increasing the number of random variables in the RVBBM modeling process, the linear relationship in formula (11) ensures that the increase in the number of variables does not have a substantial impact on the computational efficiency of uncertainty analysis.

5. EXAMPLE OF PARALLEL CABLES CROSSTALK PREDICTION

The parallel cables crosstalk prediction example proposed in [29] and [30] is used in this section to verify the performance of the combined uncertainty analysis method of the RVBBM and DRSG-SCM proposed in the previous section. The specific structure of this example is shown in Figure 4, which has 3 uncertain parameters. The first uncertainty parameter is the voltage value of the excitation source, which satisfies formulas (2) and (3). According to the RVBBM constructed in Section 2, it can also be represented by the random variables ξ_1 and ξ_2 in formula (4). The other two uncertain parameters are the height of two parallel cables, which can be described by the following random variable model:

$$\begin{cases} h_1(\xi_4) = 0.045 + 0.005 \times \xi_4\ [\text{m}] \\ h_2(\xi_5) = 0.035 + 0.005 \times \xi_5\ [\text{m}] \end{cases} \quad (12)$$

Among them, ξ_4 and ξ_5 are uniformly distributed random variables within the interval $[-1,\ 1]$. The horizontal distance between the two cables is 0.05 m, and the frequency range of the remote crosstalk results to be solved is 1 MHz to 100 MHz. All settings are the same as those in [30].

According to the RVBBM model constructed by formula (4), the input parameter random variables are determined as ξ_1, ξ_2,

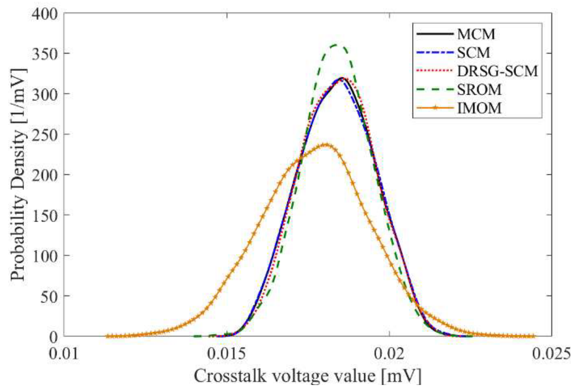

FIGURE 5. Probability density results of the crosstalk voltage value at 5 MHz.

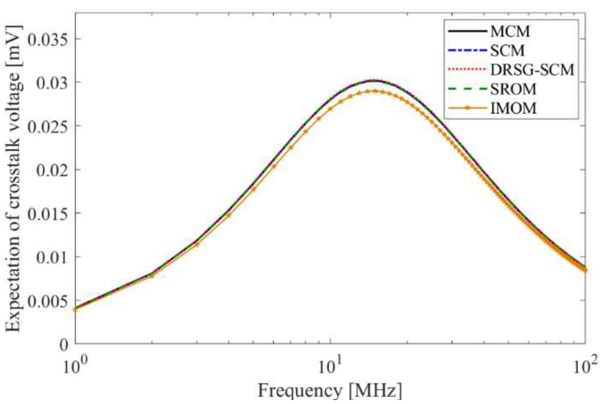

FIGURE 6. Expectation results of the crosstalk voltage value from 1 MHz to 100 MHz.

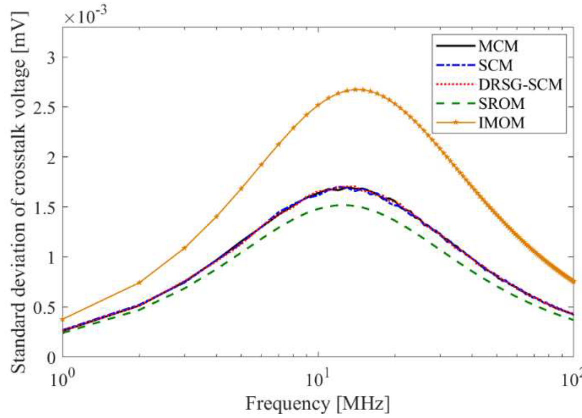

FIGURE 7. Standard deviation results of the crosstalk voltage value from 1 MHz to 100 MHz.

ξ_4, and ξ_5, with a uniform distribution of random variables in four $[-1, 1]$ intervals. According to DRSG-SCM, the Legendre polynomial is used to construct formula (8), and the zero point of the seventh order polynomial is selected for the second layer collocation points. According to formula (11), the total number of collocation points can be calculated as $4 \times (7-1)+1 = 25$.

The uncertainty analysis results of crosstalk voltage values based on the DRSG-SCM are shown in Figure 5, Figure 6, and Figure 7. As a comparison, the results of efficient uncertainty analysis methods such as SCM, SROM, and IMOM are also presented, all of which use the simulation results of MCM as standard data.

Figure 5 shows the comparison of probability density curves of remote crosstalk voltage values at 5 MHz. The simulation results of MCM are used as standard data. The common area between the probability density curves of MCM and SCM is 99%, and the common area between MCM and DRSG-SCM is 98%. Since both are greater than 95%, it indicates that the calculation accuracy of SCM and DRSG-SCM is at the "excellent" level specified in [28]. However, the common area corresponding to the SROM is only 87%, while the IMOM is 68%, which proves their poor computational accuracy.

The expectation calculation results and standard deviation calculation results of remote crosstalk voltage values from 1 MHz to 100 MHz are shown in Figure 6 and Figure 7, respectively. The Feature Selection Verification (FSV) method in computational electromagnetics is introduced in this section to quantitatively evaluate the effectiveness of simulation results [31, 32]. Similarly, MCM simulation results are used as standard data, with an FSV value of 0.017 between the MCM and SCM, 0.016 between the MCM and DRSG-SCM, 0.012 for the SROM, and 0.058 for the IMOM. According to the judgment criteria of [31], all four simulation results belong to the "excellent" level.

In the standard deviation calculation results, the FSV value between the MCM and SCM is 0.11, and the FSV value between the MCM and DRSG-SCM is 0.10, but the FSV value corresponding to the SROM is 0.24, and the FSV value corresponding to the IMOM is 0.69. According to the standards of reference [31], the calculation accuracy of the SCM and DRSG-SCM belongs to the "very good" level; the SROM only belongs to the "good" level; and the IMOM is in the "fair" level.

Therefore, the SCM and DRSG-SCM have the same computational accuracy as the MCM in parallel cable crosstalk pre-

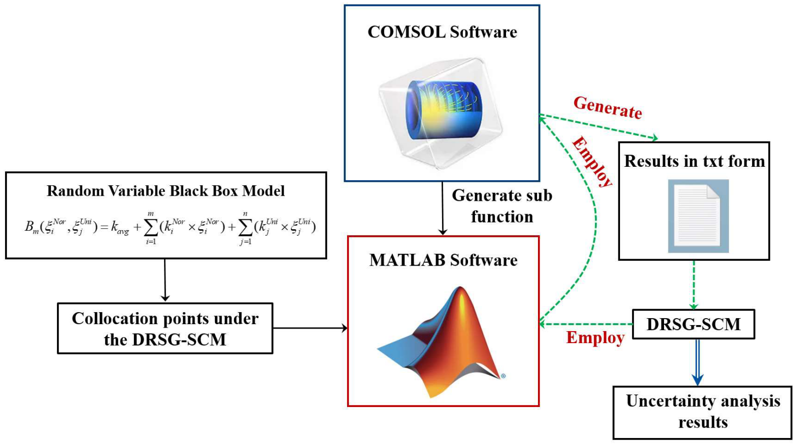

FIGURE 8. Construction of the joint simulation platform of the MATLAB software and the COMSOL software.

diction examples, while the SROM and IMOM have relatively poor computational accuracy.

In terms of computational efficiency, the 3 random variables ξ_x, ξ_4, and ξ_5 need to be processed by the MCM, and 10000 deterministic EMC simulations are conducted to ensure convergence, with a required time of 18.71 hours. 3 random variables ξ_x, ξ_4, and ξ_5 are also processed by the SCM, with the zero points of the 7th order chaotic polynomial as the collocation points. The collocation points are then combined in tensor product form, and the deterministic EMC simulation frequency is $7 \times 7 \times 7 = 343$, with a required simulation time of 0.73 hours. Only 25 deterministic EMC simulations are required by the DRSG-SCM, with a simulation time of only 2.80 minutes. 8 deterministic EMC simulations are required by the SROM, with a simulation time of 0.91 minutes. 7 deterministic EMC simulations are required by the IMOM, with a simulation time of 0.79 minutes.

In summary, DRSG-SCM is the only uncertainty analysis method that combines computational efficiency and accuracy, and can effectively solve the curse of dimensionality caused by the traditional SCM tensor product collocation point selection method. At the same time, it is also verified that RVBBM can effectively address the limitations of DRSG-SCM random variable form, in order to achieve efficient and accurate EMC simulation uncertainty analysis.

6. THE PROMOTION OF THE RVBBM IN COMSOL SOFTWARE

Many factors often need to be considered in the EMC problem of practical engineering, and the setting of geometric regions is relatively complex. Commercial finite element simulation software usually needs to be used for simulation, such as CST, COMSOL, and FEKO. Therefore, it is of great significance to effectively integrate new advanced uncertainty analysis methods with commercial simulation software.

In January 2022, COMSOL made a preliminary attempt by adding an uncertainty analysis module for the first time in its new version of 6.0 software. However, there are two problems that are always difficult to solve during use: (1) MCM and SCM are used as core algorithms, and the problem of the curse of dimensionality cannot be solved. The new uncertainty analysis method itself has poor applicability and is difficult to promote in commercial simulation software. (2) From the perspective of users, it can better help users understand the concept of uncertainty analysis and better serve practical engineering applications. For example, complex stochastic models similar to nonGaussian stochastic processes are difficult for engineers to understand and are not conducive to engineering applications.

If the uncertainty analysis method proposed in the third section of this article is adopted, RVBBM is used to construct an uncertainty model of input parameters. Engineers only need to provide a large number of sampling points that can describe the uncertainty (data can be directly obtained from experiments or generated by sampling random variables using MATLAB software), which not only reduces the probability of conceptual confusion but also solves the applicability problem of the new uncertainty analysis method. At the same time, if DRSG-SCM is used as the core algorithm for uncertainty analysis, it not only includes non-embedded features but also has many advantages such as high accuracy, high computational efficiency, and not affected by the curse of dimensionality. It is an ideal choice for commercial electromagnetic simulation software at present.

To promote the uncertainty analysis method in Section 3, the joint simulation debugging of the COMSOL software and MATLAB software needs to be implemented first. An RVBBM model needs to be constructed and implemented in MATLAB software for two-layer collocation points calculation under the dimensionality reduction sparse grid strategy. Then, deterministic EMC simulation on the collocation points is implemented in COMSOL software, and the deterministic simulation results are returned to MATLAB software for uncertainty analysis based on DRSG-SCM.

The construction method of the joint simulation platform is shown in Figure 8, and the following two key technologies are highlighted:

(1) The assignment problem of collocation points. If it is a parameter of a numerical variable, it can be directly as-

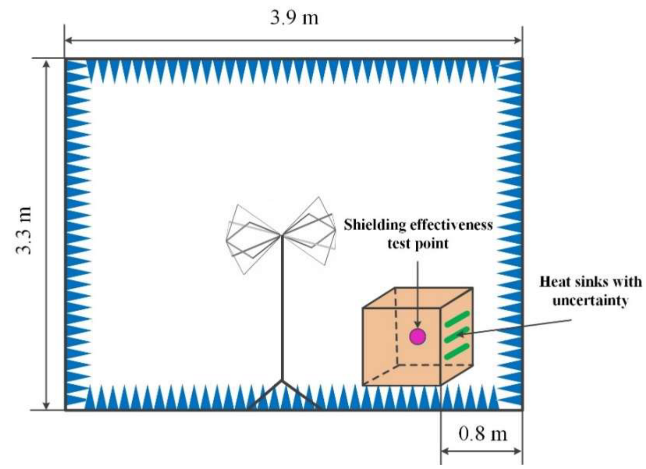

FIGURE 9. Calculation example of shielding effectiveness of metal box.

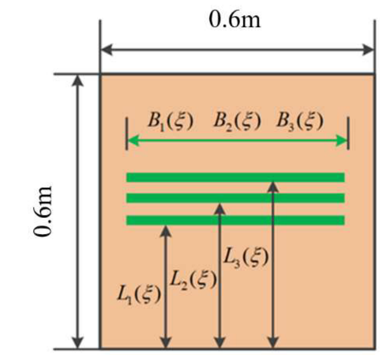

FIGURE 10. Enlarged view of the heat dissipation holes on the metal box.

signed. If it is a parameter of a character variable, it needs to be assigned using the num2str function in MATLAB software.

(2) The data transmission between COMSOL software and MATLAB software relies on "TXT" files. If MATLAB software needs to read deterministic EMC simulation results data from TXT files, pointer programming can be used to delete useless information lines. For example, the following program can read data and delete the first 8 lines of information,

1 — fid = fopen (strcat ('EMC_results', '.txt')),

2 — data = textscan (fid, '%f', 'HeaderLines', 8).

Next, an example of the shielding effectiveness of a metal box will be proposed to verify the effectiveness of the joint simulation scheme proposed in this section. The specific situation of the calculation example is shown in Figure 9, where the test antenna and metal shielding box are stored in an anechoic chamber. The size of the darkroom is $3.9 \times 3.9 \times 3.3\,\mathrm{m}^3$, and its shielding material is low conductivity carbon loaded foam. The Bi-Cone test antenna is located in the center of the darkroom and emits spherical electromagnetic waves ranging from 1 MHz to 10 MHz.

On the right side of the anechoic chamber, there is a metal aluminum box with a size of $0.6 \times 0.6 \times 0.6\,\mathrm{m}^3$. The rightmost end of the box is 0.8 m away from the right wall. The skin thickness of the metal box is 0.02 m, and the center of the box is the shielding effectiveness testing point. The shielding effectiveness calculation formula is as follows:

$$SE = 20\log_{10}\left(\frac{E_{no-box}}{E_{with-box}}\right)\,[\mathrm{dB}] \tag{13}$$

Among them, E_{no-box} is the simulated electric field strength value at the test point position when the metal box does not exist, and $E_{with-box}$ is the electric field strength value when the metal box exists.

There are 3 heat dissipation holes on the right side of the metal box, and their enlarged view is shown in Figure 10. Assuming that the dimensions of these holes are uncertain, the following relationship is met:

$$\begin{cases} L_1(\xi) = 0.22 + 0.05 \times \xi_6\,[\mathrm{m}] \\ L_2(\xi) = 0.3 \times (1 + 0.1 \times \xi_y)\,[\mathrm{m}] \\ L_3(\xi) = 0.38 + 0.05 \times \xi_7\,[\mathrm{m}] \\ B_1(\xi) = 0.4 + 0.02 \times \xi_8\,[\mathrm{m}] \\ B_2(\xi) = 0.4 + 0.02 \times \xi_9\,[\mathrm{m}] \\ B_3(\xi) = 0.4 + 0.02 \times \xi_{10}\,[\mathrm{m}] \end{cases} \tag{14}$$

Among them, ξ_y is a random variable that satisfies formula (6), and ξ_6, ξ_7, ξ_8, ξ_9, and ξ_{10} are all normally distributed random variables.

By applying RVBBM, parameter $L_2(\xi)$ can be converted as follows:

$$L_2(\xi) = 0.3 \times (1.202 + 0.051 \times \xi_3)\,[\mathrm{m}] \tag{15}$$

Among them, ξ_3 is a normally distributed random variable, and this transformation is derived from formula (7).

The uncertainty analysis results of shielding effectiveness obtained by applying the joint simulation scheme proposed in this section are shown in Figure 11 and Figure 12. There are 6 random variables in the simulation model, and the number of sampling points required for the MCM is too high, resulting in a high time cost that cannot be achieved. Therefore, in this case, the SCM simulation results are used as standard data.

For the expected value results shown in Figure 11, FSV method is also used. The FSV value between DRSG-SCM and SCM is 0.0062; the FSV value corresponding to SROM is 0.0037; and the FSV value corresponding to IMOM is 0.0066, all of which belong to the "excellent" level. Back to the standard deviation results shown in Figure 12, the FSV value between DRSG-SCM and SCM is 0.15, proving that the calculation accuracy of DRSG-SCM belongs to the "very good" level. The FSV value corresponding to SROM is 0.56, which only belongs to the "fair" level. The FSV value corresponding to IMO is 0.98, even in the "poor" level.

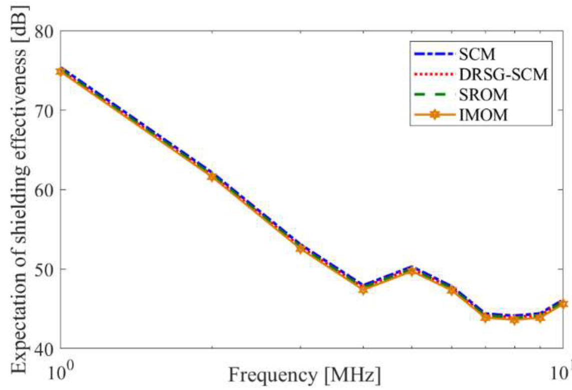

FIGURE 11. Expectation results of shielding effectiveness of metal box.

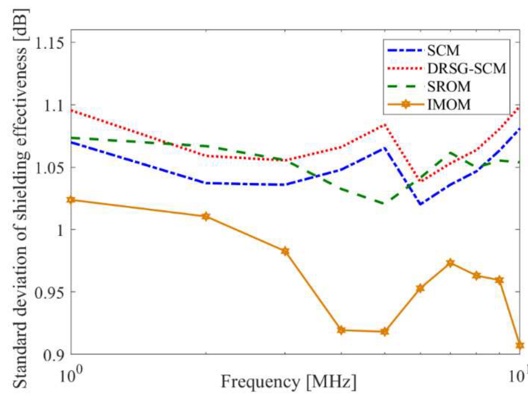

FIGURE 12. Standard deviation results of shielding effectiveness of metal box

In summary, the calculation accuracy of DRSG-SCM is at the same level as that of SCM, while the calculation accuracy of SROM and IMOM is poor.

For the DRSG-SCM under RVBBM model, there are 6 random variables, including ξ_3, ξ_6, ξ_7, ξ_8, ξ_9, and ξ_{10}, all of which follow a normal distribution. According to formula (8), the Hermitian polynomial is selected to construct the collocation point, and the zero point of the 7th order polynomial is also used as the second layer collocation point. The number of deterministic EMC simulations required for the DRSG-SCM is $6 \times (7-1)+1 = 37$. For SCM, the random variables that it needs to handle are 6, including ξ_y, ξ_6, ξ_7, ξ_8, ξ_9, and ξ_{10}. The zeros of the 4th order chaotic polynomial are selected to construct the tensor product form of the settlement point, and the number of deterministic EMC simulations required is $4^6 = 4096$. When simulating the shielding effectiveness of the metal box, the simulation time required to achieve DRSG-SCM is 2.33 hours, while the simulation time required for SCM is 10.68 days.

Therefore, DRSG-SCM can achieve the same computational accuracy as SCM with less than 1% of the computational resources used. The significant advantages of the DRSG-SCM in dealing with high-dimensional random variable problems are fully demonstrated.

In summary, by implementing the joint simulation technology of COMSOL software and MATLAB software, RVBBM and DRSG-SCM are promoted to the application of commercial electromagnetic simulation software in this section, verifying that the modeling approach based on RVBBM can effectively assist in the implementation and promotion of various new uncertainty analysis methods in commercial simulation software in the future.

7. THE OUTLOOK OF THE RVBBM

The theoretical basis of the RVBBM modeling method is the Bayesian neural network model. However, in the model constructed in this article, the nonlinear threshold calculation of neurons is ignored, as shown in formula (1). The core idea of this article is to conduct joint uncertainty analysis with the DRSG-SCM, so this part is ignored. If non-linear threshold calculation is introduced into formula (1), it will definitely improve the ability of the RVBBM to handle nonlinearity in practical engineering. For example, the numerical calculation of singular fields in Reference [33], or the simulation of dipole antennas in Reference [34]. The effectiveness of this part can be discussed in detail in subsequent research.

Meanwhile, in the modeling process of the RVBBM, only a portion of random variables are considered. In subsequent research, it can be replaced with other random variable models, even random fuzzy variable models, fractal dimension variable models, and random process variable models. The impact of improvements in this section on the performance of RVBBM can also be discussed in detail in subsequent research.

8. CONCLUSION

Based on the MEAM and genetic algorithm, an uncertainty input modeling method for electromagnetic compatibility simulation called random variable black box model is proposed in this paper. This method can directly model a large amount of sampling points data to effectively avoid simulation errors caused by researchers confusing the concept of uncertainty. A random variable black box model method is applied to DRSG-SCM, and the limitations of the use condition of the dimensionality reduction sparse grid strategy "probability density function must be symmetric about the y-axis" are solved. Efficient uncertainty analysis of electromagnetic compatibility simulation under high-dimensional random variables is achieved, and the problem of the curse of dimensionality is fundamentally solved. By using the computational electromagnetic feature selection verification method, this performance is effectively verified in parallel cable crosstalk examples and metal box shielding effectiveness examples. Finally, the joint simulation technology of MATLAB software and COMSOL software is implemented in this paper. The random variable black box model and DRSG-SCM are applied to commercial electromagnetic simulation software, verifying the strong portability of random variable black box model and ensuring the effective promotion of various new uncertainty analysis methods in commercial electromagnetic simulation software, in order to broaden the application scope of uncertainty analysis.

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REFERENCES

[1] Pignari, S. A., G. Spadacini, and F. Grassi, "Modeling field-to-wire coupling in random bundles of wires," *IEEE Electromagnetic Compatibility Magazine*, Vol. 6, No. 3, 85–90, Nov. 2017.

[2] Xie, H., J. F. Dawson, J. Yan, A. C. Marvin, and M. P. Robinson, "Numerical and analytical analysis of stochastic electromagnetic fields coupling to a printed circuit board trace," *IEEE Transactions on Electromagnetic Compatibility*, Vol. 62, No. 4, 1128–1135, 2019.

[3] De Menezes, L. R. A. X., D. W. P. Thomas, C. Christopoulos, A. Ajayi, and P. Sewell, "The use of unscented transforms for statistical analysis in EMC," in *2008 International Symposium on Electromagnetic Compatibility-EMC Europe*, 1–5, IEEE, 2008.

[4] Zhang, Y., C. Liao, R. Huan, Y. Shang, and H. Zhou, "Analysis of nonuniform transmission lines with a perturbation technique in time domain," *IEEE Transactions on Electromagnetic Compatibility*, Vol. 62, No. 2, 542–548, 2019.

[5] Gillman, A., A. H. Barnett, and P.-G. Martinsson, "A spectrally accurate direct solution technique for frequency-domain scattering problems with variable media," *BIT Numerical Mathematics*, Vol. 55, No. 1, 141–170, 2015.

[6] Edwards, R. S., A. C. Marvin, and S. J. Porter, "Uncertainty analyses in the finite-difference time-domain method," *IEEE Transactions on Electromagnetic Compatibility*, Vol. 52, No. 1, 155–163, 2009.

[7] Ajayi, A., P. Ingrey, P. Sewell, and C. Christopoulos, "Direct computation of statistical variations in electromagnetic problems," *IEEE Transactions on Electromagnetic Compatibility*, Vol. 50, No. 2, 325–332, May 2008.

[8] Manfredi, P., D. V. Ginste, I. S. Stievano, D. D. Zutter, and F. Canavero, "Stochastic transmission line analysis via polynomial chaos methods: An overview," *IEEE Electromagnetic Compatibility Magazine*, Vol. 6, No. 3, 77–84, Nov. 2017.

[9] Manfredi, P., D. V. Ginste, D. D. Zutter, and F. Canavero, "Generalized decoupled polynomial chaos for nonlinear circuits with many random parameters," *IEEE Microwave and Wireless Components Letters*, Vol. 25, No. 8, 505–507, Aug. 2015.

[10] Manfredi, P. and F. G. Canavero, "Polynomial chaos for random field coupling to transmission lines," *IEEE Transactions on Electromagnetic Compatibility*, Vol. 54, No. 3, 677–680, Jun. 2012.

[11] Wu, T.-L., F. Buesink, and F. Canavero, "Overview of signal integrity and EMC design technologies on PCB: Fundamentals and latest progress," *IEEE Transactions on Electromagnetic Compatibility*, Vol. 55, No. 4, 624–638, Aug. 2013.

[12] Manfredi, P., "A hierarchical approach to dimensionality reduction and nonparametric problems in the polynomial chaos simulation of transmission lines," *IEEE Transactions on Electromagnetic Compatibility*, Vol. 62, No. 3, 736–745, Jun. 2019.

[13] Cui, C. and Z. Zhang, "High-dimensional uncertainty quantification of electronic and photonic IC with non-gaussian correlated process variations," *IEEE Transactions on Computer-Aided Design of Integrated Circuits and Systems*, Vol. 39, No. 8, 1649–1661, Jun. 2019.

[14] Konakli, K. and B. Sudret, "Polynomial meta-models with canonical low-rank approximations: Numerical insights and comparison to sparse polynomial chaos expansions," *Journal of Computational Physics*, Vol. 321, 1144–1169, Sep. 2016.

[15] Doostan, A., A. Validi, and G. Iaccarino, "Non-intrusive low-rank separated approximation of high-dimensional stochastic models," *Computer Methods in Applied Mechanics and Engineering*, Vol. 263, 42–55, Aug. 2013.

[16] Fei, Z., Y. Huang, J. Zhou, and Q. Xu, "Uncertainty quantification of crosstalk using stochastic reduced order models," *IEEE Transactions on Electromagnetic Compatibility*, Vol. 59, No. 1, 228–239, Feb. 2016.

[17] Bai, J., G. Zhang, L. Wang, and T. Wang, "Uncertainty analysis in EMC simulation based on improved method of moments," *The Applied Computational Electromagnetics Society Journal (ACES)*, Vol. 31, No. 1, 66–71, Jan. 2016.

[18] Bai, J., G. Zhang, A. P. Duffy, and L. Wang, "Dimension-reduced sparse grid strategy for a stochastic collocation method in EMC software," *IEEE Transactions on Electromagnetic Compatibility*, Vol. 60, No. 1, 218–224, 2017.

[19] Wang, Y., D. Zhang, S. Zhang, H. Wang, and S. Cong, "VLSI circuit measurement system analysis based on random fuzzy variables," in *2018 Eighth International Conference on Instrumentation & Measurement, Computer, Communication and Control (IMCCC)*, 1096–1100, IEEE, 2018.

[20] Bellan, D. and S. A. Pignari, "Efficient estimation of crosstalk statistics in random wire bundles with lacing cords," *IEEE Transactions on Electromagnetic Compatibility*, Vol. 53, No. 1, 209–218, Feb. 2011.

[21] Cui, C. and Z. Zhang, "Stochastic collocation with non-gaussian correlated process variations: Theory, algorithms, and applications," *IEEE Transactions on Components, Packaging and Manufacturing Technology*, Vol. 9, No. 7, 1362–1375, 2018.

[22] Bao, Y., J. M. Velni, and M. Shahbakhti, "Epistemic uncertainty quantification in state-space LPV model identification using bayesian neural networks," *IEEE Control Systems Letters*, Vol. 5, No. 2, 719–724, Jun. 2020.

[23] Li, H., P. Barnaghi, S. Enshaeifar, and F. Ganz, "Continual learning using bayesian neural networks," *IEEE Transactions on Neural Networks and Learning Systems*, Vol. 32, No. 9, 4243–4252, 2020.

[24] Jia, X., J. Yang, R. Liu, X. Wang, S. D. Cotofana, and W. Zhao, "Efficient computation reduction in bayesian neural networks through feature decomposition and memorization," *IEEE Transactions on Neural Networks and Learning Systems*, Vol. 32, No. 4, 1703–1712, 2020.

[25] Sun, Y., B. Xue, M. Zhang, G. G. Yen, and J. Lv, "Automatically designing CNN architectures using the genetic algorithm for image classification," *IEEE Transactions on Cybernetics*, Vol. 50, No. 9, 3840–3854, Sep. 2020.

[26] Choi, K., D.-H. Jang, S.-I. Kang, J.-H. Lee, T.-K. Chung, and H.-S. Kim, "Hybrid algorithm combing genetic algorithm with evolution strategy for antenna design," *IEEE Transactions on Magnetics*, Vol. 52, No. 3, 1–4, 2015.

[27] Ha, B. V., M. Mussetta, P. Pirinoli, and R. E. Zich, "Modified compact genetic algorithm for thinned array synthesis," *IEEE Antennas and Wireless Propagation Letters*, Vol. 15, 1105–1108, Oct. 2015.

[28] Bai, J., L. Wang, D. Wang, A. P. Duffy, and G. Zhang, "Validity evaluation of the uncertain EMC simulation results," *IEEE Transactions on Electromagnetic Compatibility*, Vol. 59, No. 3, 797–804, 2016.

[29] Bai, J., J. Sun, and N. Wang, "Convergence determination of emc uncertainty simulation based on the improved mean equivalent area method," *The Applied Computational Electromagnetics Society Journal*, Vol. 36, No. 11, 1446–1452, Nov. 2021.

[30] Bai, J., G. Zhang, D. Wang, A. P. Duffy, and L. Wang, "Performance comparison of the SGM and the SCM in EMC simulation," *IEEE Transactions on Electromagnetic Compatibility*, Vol. 58, No. 6, 1739–1746, Dec. 2016.

[31] Duffy, A. P., A. Orlandi, and G. Zhang, "Review of the feature selective validation method (FSV). Part I-Theory," *IEEE Transactions on Electromagnetic Compatibility*, Vol. 60, No. 4, 1–8, Aug. 2018.

[32] Orlandi, A., A. P. Duffy, and G. Zhang, "Review of the feature selective validation method (FSV). Part II - Performance analysis and research fronts," *IEEE Transactions on Electromagnetic Compatibility*, Vol. 60, No. 4, 1029–1035, Aug. 2018.

[33] Valagiannopoulos, C. A., "On smoothening the singular field developed in the vicinity of metallic edges," *International Journal of Applied Electromagnetics and Mechanics*, Vol. 31, No. 2, 67–77, Sep. 2009.

[34] Fikioris, G. and C. Valagiannopoulos, "Input admittances arising from explicit solutions to integral equations for infinite-length dipole antennas," *Progress In Electromagnetics Research*, Vol. 55, 285–306, 2005.