Inter-System EMC Prediction with CG-GRBF Networks

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Keywords: EMC prediction, Generalized RBF Networks, Conjugate gradient method.

Abstract. With the development of electronic technology, electromagnetic compatibility (EMC) becomes more and more important, and the EMC prediction is one of the most crucial EMC procedures. However, the EMC prediction is strongly non-linear and uneven, so it is tremendously hard to use traditional methods to conduct such prediction. To solve problems above, intelligent algorithms are introduced in our work to make EMC prediction. A general CG-GRBF Network is raised in this essay with a combination of Generalized RBF Networks (Radial Basis Function Networks) and the Conjugate Gradient Method (CG), which optimizes a selection of the standard deviation of the radial basis function. A contrast experiment among CG-GRBF, BP and GRBF networks is conducted and it turns out that the CG-GRBF Network is much better than the other two networks. Thus, the CG-GRBF Network can be one of the best choices to conduct the EMC prediction.

Introduction

Oriented from the electromagnetic interference (EMI), the EMC problems attracted great attention of worldwide researchers in the 20th century and will never be obsolete [1]. Nowadays, with the rapid development of computer science, EMC problems have become more and more important and sophisticated. As the EMC prediction is one of the essential procedures to achieve electromagnetic compatibility, it will save more resources, if creators carrying out EMC prediction during its period of design instead of mending products after its electromagnetic crash.

To realize EMC prediction, many numerical methods were raised, for example, Moment method, Finite element method, and Finite difference time domain method [2]. However, it is extremely hard to find out clear relationship of the EMC between systems because of the complicated interaction among these systems, so traditional algorithms above failed to handle modern electromagnetic environment. On the other hand, as a kind of new algorithm first put up in 1980s, Neural Networks have already made great achievements in fitting functions, for which researchers began to attach Neural Networks to EMC prediction. Mr. Li Yongming proposed the Artificial Neural Networks (ANN) Technology of EMC Prediction [3] in 2008, and established a model based on the crosstalk of double parallel rails and eventually obtained 36 groups of data, which were afterwards fit by traditional Back Propagation Neural Networks (BPNN). From 2009 to 2011, Mr. Chen Shuwen and his colleagues constantly applied improved BPNN to this problem [4, 5, 6, 7]. In 2016, a group led by Chetan trained BPNN with 7 different learning algorithms [8], utilized it to make EMC prediction, and checked the results with measured data. Although the efforts above made great sense, the relatively simple data they utilized could not actually reflect the complexity of EMC prediction. If Neural Networks can be trained with EMI data between systems which are simulated with electromagnetic numeral calculation, a measure will be given when taking in a new set of electromagnetic parameters, thus finding the EMC.

The paper proposes General CG-RBF Networks, and applies it to EMC prediction. Arbitrary 100 groups of electromagnetic signals out of 1000 serve as the testing set, and the left 900 groups work as the training set to build the Network. The results are marked with Mean Squared Error (MSE) and Mean Relative Error (MRE) as characteristics. The paper makes a comparison among General CG-RBF Networks, BPNN, and General RBF Networks, and eventually comes to the conclusion that the General CG-RBF Networks wins the first place of accuracy and gets a significant improvement.
Therefore, the General CG-RBF Networks can be an excellent tool to conduct EMC prediction, which somehow shows a few instructions for further study.

**EMC between Systems**

From the 1970s onwards, people had in-depth study of the EMC theory worldwide, establishing a variety of prediction models, and putting forward a number of numerical methods of prediction models for solving the electromagnetic problem.

The three elements of EMC research are electromagnetic interference sources, coupling paths and sensitive devices. In the prediction analysis of EMC between systems, the launch system consists of transmitter and transmitter antenna and the receiving system by the receiver and the receiving antenna. The basic equations of EMC analysis between systems: For a pair of transmitter and receiver, the interference can be determined by comparing the interference power value received by the receiver with the sensitivity threshold [9]. The difference between the interference input and the sensitivity threshold at the receiver input is called the interference margin [9, 10, 11], which is

\[
IM(f, t, d, p) = P_T(f, t, d, p) - P_S(f, t) - L(f, t, d, p) - P_S(f, t)
\]

The EMC of the system can be further described in detail from factors such as transmitters, receivers, propagation losses, and transmit and receive antennas [10]. Considering a detailed description of the inter-frequency, time, distance between the receiving antenna and the receive antenna relative direction in the formula, we obtain a more detailed equation of prediction of the EMC between systems [10]:

\[
IM(f_R, t, d, p) = P_T(f_T, t) + G_T(f_T, t, d, p) + G_S(f_R, t, d, p) - P_S(f_R, t) - L(f_T, t, d, p) + CF(B_T, B_R, \Delta f, t) + \Delta G
\]

where \( IM \) represents the electromagnetic interference margin, \( P_T \) represents the transmit power of the transmitter, \( G_T \) indicates the transmitter antenna gain, \( G_S \) represents the receiver antenna gain, \( P_S \) represents the receiver's sensitivity threshold at frequency \( f_R \), \( L \) indicates transmission loss, \( CF \) means to consider the transmitter bandwidth \( B_T \), receiver bandwidth \( B_R \), correction of frequency interval \( \Delta f \), and \( \Delta G \) refers to the antenna gain strength, polarization, etc. considering the amendment.

If \( IM > 0 \), it indicates that there is potential interference; if \( IM < 0 \), it means that there is no interference. It comes to a critical state if \( IM = 0 \).

In practice, multiple transmitters and receivers are often arranged in the same area, and there are a variety of coupling paths. At the time of EMC prediction, each transmitter, a receiver and a coupling path are selected to form a "transmit-response pair" to predict progressively. If the constructed neural network can fit the interference level of a single "transmit-response pair", then the network has the ability to make EMC predictions between systems.

**CG-GRBF Networks**

**GRBF Networks**

![Generalized radial basis function networks](image)

Figure 1. Generalized radial basis function networks.
Generalized Radial Basis Function (GRBF) networks were firstly introduced by Moody and Darken in 1988 [12]. Unlike the RBF networks, the number of hidden layer nodes in a GRBF network is much lesser than the sample size. This structure ensures GRBF networks’ feasibility even when dealing with large sample of data.

In a GRBF network, there are m nodes in the input layer, equaling to the dimension of input vectors. Hidden layer consisted of K nodes, K < P, in which P stands for the sample size. Output layer has only one node. The transfer function from input layer to hidden layer is radial basis function (RBF), which is a scalar function has radial symmetry. RBFs are usually represented by \( \phi(r) = e^{-\frac{r^2}{\sigma^2}} \), in which ||\( r \)|| is norm and \( e \) stands for the center of \( \phi \). In this paper, Gaussian function \( \phi(r) = e^{-\frac{r^2}{\sigma^2}} \) will be used as a radial basis function.

To build a GRBF network, there are three parameters need to be fixed.

**Centers.** The number of hidden nodes is not equal to the sample size, which means the samples can’t be assigned respectively to a hidden node, or in other words, a radial basis function. So clustering methods should be applied to separate the samples into \( K \) clusters. Then the centers of these \( K \) clusters will be used as the centers of \( K \) hidden nodes. The following algorithm "K-medoids" will be utilized for clustering in our work.

Randomly pick \( K \) points from all the samples as the initial centers.

For every input sample \( x_i \) \( \{i=1, 2, \ldots, P\} \), find \( c_{\min} \) from all the initial centers such that \( \|c_{\min} - x_i\|^2 = \min_{j=1, \ldots, K} \|c_j - x_i\|^2 \) and assign \( x_i \) to the cluster that regards \( c_{\min} \) as its center.

For every cluster, choose a new center \( c' \) from all the samples \( \{x_1, x_2, \ldots, x_P\} \) in this cluster such that \( c' = \arg\min_{x_i} \sum_{j=1, j\neq i}^h \|x_i - x_j\|^2 \).

If centers don’t change then return all the \( c' \), otherwise start next iteration from the second step.

**Standard Deviation.** Generally, standard derivations are derived from empirical formula. A natural and popular method is to consider the distances between centers and evaluate standard deviations in a self-organized way. For instance, compute the minimum distance from other centers to \( c_i \) and get \( \sigma_i \) using the formula \( \sigma_i = \lambda d_i \), in which \( d_i = \min_{j=1,2,\ldots,m,j\neq i} \|c_i - c_j\| \). \( \lambda \) is called overlap coefficient, usually set as \( \lambda = 1 \).

**Weights.** The goal of training is to enable the GRBF network of fitting training sets and testing samples well. However, testing samples are unavailable during the training of networks. Thus using the least square method, the target function can be naturally written as \( E(f) = \frac{1}{2} \sum_{i=1}^P (y_i - f(x_i))^2 \) and the problem is to find a proper GRBF network \( f \) to minimize \( E(f) \).

As we know from GRBF networks’ structure, there is \( f(x_i) = \sum_{j=1}^K \omega_j e^{\frac{\|x_i - c_j\|^2}{\sigma_j^2}} = y_i \), \( i = 1, 2, \ldots, P \). It can be rewritten in the following matrix form \( \Phi W = Y \), in which

\[
\Phi = \begin{pmatrix}
\frac{1}{\|x_1-c_1\|^2} & \cdots & \frac{1}{\|x_1-c_K\|^2} \\
\frac{1}{\|x_2-c_1\|^2} & \cdots & \frac{1}{\|x_2-c_K\|^2} \\
\vdots & \ddots & \vdots \\
\frac{1}{\|x_P-c_1\|^2} & \cdots & \frac{1}{\|x_P-c_K\|^2}
\end{pmatrix},
W = (\omega_1, \ldots, \omega_K)^T, Y = (y_1, \ldots, y_P)^T.
\]

Obviously \( E(f) = \frac{1}{2} (\Phi W - Y)^T (\Phi W - Y) \) is a convex quadratic function of \( W \), so the minimum point satisfies \( W = \Phi^* Y = (\Phi^T \Phi)^{-1} \Phi^T Y \), in which \( \Phi^* \) is the generalized inverse of \( \Phi \). \( \Phi \) and \( Y \) are fixed values with given training sets, so the optimal \( W \) can be calculated by \( W = \Phi^* Y \).

Till then, GRBF networks can be easily set up by arbitrary input training samples.

**Conjugated Gradient Method**
Conjugated Gradient Method (CG method) was firstly put forward by Hestenes and Stiefel in 1952 [13], and was utilized to solve linear equations. 12 years later, Fletcher and Reeves primarily applied
CG method in the minimization of ordinary non-linear function [14]. Thus, CG method became well-known as a popular optimization algorithm. Because calculating or storing the Hessian matrix is unnecessary in optimization, CG method turns out to be an algorithm with fast convergence and the ability to solve large-scale problems.

Several variants of CG method can be derived due to the differences in calculating conjugated vectors. One of those methods called Fletcher-Reeves (FR) CG method will be used in our work. Concrete steps are as follows.

Fix initial point \( x^{(0)} \) and starting gradient \( g^{(0)} = \nabla f(x^{(0)}) \), let \( p^{(0)} = g^{(0)} \), \( k = 0 \) and set \( \varepsilon \).

If \( \| g^{(0)} \| \leq \varepsilon \) then stop iteration, otherwise calculate the step size \( \alpha_k \) of line search by Backtracking-Armijo criterion and set \( x^{(k+1)} = x^{(k)} + \alpha_k p^{(k)} \).

Let \( g^{(k+1)} = \nabla f(x^{(k+1)}) \) and \( p^{(k+1)} = g^{(k+1)} + \frac{g^{(k+1)} T \cdot g^{(k+1)}}{g^{(k)} T \cdot g^{(k)}}, \)

Update \( k = k + 1 \) and go to the second step.

**CG-GRBF Networks**

During the training of GRBF networks, or in other words, the optimization of parameters, the centers of RBFs can be calculated by clustering algorithms and the weights are computable with the help of least square method. However, drawing support from empirical formulas is the only way to evaluate standard derivations.

In the previous chapters, an expression of \( f \) can be converted into a minimization problem \( \min_{\sigma} \, Y^T \Phi (\Phi^T \Phi)^{-1} \Phi^T Y \) in which \( \Phi = \Phi(\sigma) \). It’s a natural thought that utilize CG method to optimize \( \sigma \) and minimize \( f \). The problem is that the gradient \( g^{(k)} \) has to be determined in \( k \)th iteration. However, it can be decidable through tedious derivation of matrix. As for the initial point \( \sigma^{(0)} \), it can be randomly picked or use the help of empirical formulas.

The training of CG-GRBF networks actually consists of three parts: to determine the centers, standard derivations and weights. The following procedure is an overview of the training process.

Determine the number of nodes of input and output layer through dimensions of input training samples, set the number of RBF centers.

Get RBF centers \( c_i \) \( (i=1, 2, \cdots, K) \) by K-medoids algorithm.

Calculate standard derivations \( \sigma_i \) \( (i=1, 2, \cdots, K) \) and \( \Phi \) using CG method.

Derive \( \Phi \) from \( \Phi = \Phi^+ Y \). Here is the end of training.

Compute the output of CG-GRBF network with the testing samples.

Compare the output obtained in the fifth step with the expected output, return the mean squared error (MSE) and mean relative error (MRE).

**Experimental Results and Analysis**

**Data Illustration**

For the convenience of calculation, we make appropriate simplification according to actual situation and the model of inter-system EMC in section 2. For a pair of transmitter and receiver, we select 14 parameters to describe it, such as firing frequency and the rated power of the transmitter etc. And we choose interference margin of fundamental wave as the characterization of electromagnetic compatibility. Eventually, we obtain a 15-dimensional vector as a concise description of real EMC system.

We get 1000 groups of data as experimental data through simulation on the base of the detailed equation of prediction of the EMC in section 2 and empirical models. We extract 900 groups as training sets, and leave the remainder to be testing samples. The original data are not listed here, and detailed data can be obtained upon author’s request.
Preliminary

To test the prediction effect of CG-GRBF network, a contrast experiment among CG-GRBF BP and GRBF networks is conducted. The BP and RBF networks are classical, both of which have certain capacity in data fitting, while the GRBF network averts the problem of ill-conditioned matrix, which often occur in RBF networks, thus the GRBF network performs better than RBF in general cases. We record the mean squared error $mse=\frac{1}{100}\sum_{i=1}^{100}(\hat{y}_i-y_i)^2$ and mean relative error $mre=\frac{1}{100}\sum_{i=1}^{100}\frac{|\hat{y}_i-y_i|}{y_i}$ during the experiment, where $\hat{y}_i$ represents the prediction output of the network corresponding to $x_i$, and the size of test data sets is 100.

Before the training, it is necessary to normalize the data, and the method we adopt is $y=\frac{x-x_{min}}{x_{max}-x_{min}}$. Applying an inverse operation to the output can transform the needed data back, and the inverse formula is $x=x_{min}+y(x_{max}-x_{min})$.

Experimental Performance

We build the BP, GRBF and CG-GRBF networks respectively by using the 900 groups of training data, and investigate the performance of each network through comparing predicted results with the test data. The prediction biases are shown in Fig 2 below.

![Figure 2. Prediction absolute error of three networks.](image)

Table 1. MSE and MRE of three networks.

<table>
<thead>
<tr>
<th>Network</th>
<th>Mean squared error (MSE)</th>
<th>Mean relative error (MRE)</th>
</tr>
</thead>
<tbody>
<tr>
<td>BP network</td>
<td>419.9483</td>
<td>20.28%</td>
</tr>
<tr>
<td>GRBF network</td>
<td>329.1940</td>
<td>12.28%</td>
</tr>
<tr>
<td>CG-GRBF network</td>
<td>246.9686</td>
<td>10.37%</td>
</tr>
</tbody>
</table>

The detail results are shown in the Table1. It is easy to be seen from the figure that the prediction biases of the BP network are all quite large, and comparatively speaking, the prediction of GRBF network and CG-GRBF network are more accurate. Both of their biases float in a small range. However, it is hard to distinguish which of the GRBF and the CG-GRBF network is better in Fig.2, while it becomes apparent when refer to table1. It is clear that the MSE of the CG-GRBF network is much smaller than that of the GRBF network.

We can conclude that the BP network has some disadvantages in the prediction of the EMC, despite its well performance in function approximation. While the GRBF Network performs relatively better but not much. Hence there is place for us to improve it. Based on GRBF Network, the CG-GRBF network makes further efforts to optimize a selection of parameters, leading to a manifest improvement in prediction accuracy.

Though some progress in applying artificial neural network and other intelligent algorithm to EMC prediction have been made, there are still deficiencies, such as the prediction is not accurate enough or the robustness is not guaranteed. CG method turns out to be an algorithm with fast convergence and the ability to solve large-scale problems, but it cannot always find the global optimal solutions. Therefore the direction of future improvement mainly lies in the two aspects as follows:
Consider combining principles of other optimization algorithms with CG method to avoid falling into local optimum. Some researchers have been working on it, and it is believed that applying the improved CG-GRBF network to the EMC prediction is foreseeable.

Apply other signal processing methods to the pretreatment of original electromagnetic signals. There are noises in electromagnetic signals, which makes the signals unsmooth. Hence combination with noise reduction or other deeper signal processing method will lead to higher quality of signals and more accurate prediction.

**Conclusion**

Based on the features of EMC problems between systems and the severe electromagnetic environment, the paper proposes the CG-GRBF Networks method to make EMC prediction. Combining the advantages of Neural Networks and Conjugate Gradient, the new approach shares the ability of good approximation and quick convergence. The Networks are trained with 1000 groups of measured data, and make a comparison with other two traditional methods. The results indicate that the CG-GRBF Networks get great advantages over other methods in fitting electromagnetic signals, and that the new method is suitable for the EMC prediction problems.

**Acknowledgments**

This work is supported by the National Natural Science Foundation of China under grants 61771001.

**Reference**


