# Modeling of 3-D Vertical Interconnect Using Support Vector Machine Regression

Lei Xia, Jicheng Meng, Ruimin Xu, Bo Yan, and Yunchuan Guo

*Abstract*—**In this letter, the support vector machine (SVM) regression approach is introduced to model the three-dimensional (3-D) high density microwave packaging structure. The SVM is based on the structural risk minimization principle, which leads to a good generalization ability. With a 3-D vertical interconnect used as an example, the SVM regression model is electromagnetically developed with a set of training data and testing data, which is produced by the electromagnetic simulation. Experimental results suggest that the developed model performs with a good predictive ability in analyzing the electrical performance.**

*Index Terms*—**Fuzz button, low temperature co-fired ceramic (LTCC), support vector machine (SVM), support vector regression (SVR), three-dimensional (3-D) vertical interconnect.**

## I. Introduction

WITH the increasing demands of compact, cost efficient, and reliable microwave modules, three-dimensional (3-D) low temperature co-fired ceramic (LTCC) technology is growing rapidly as one of the most efficient solutions. It is characterized with the complex configuration including stacked substrates, vertical transitions, and solder-less interconnects, etc. [1]. Accurate modeling of these complex structures and fast and effective design tools are required for the designing of microwave circuits. Full-wave electromagnetic (EM) simulations are typically computationally accurate but time-consuming, especially for adjustment of design and optimization. The methods of modeling based on sampling data such as artificial neural network (ANN) are widely applied in recent years for its nonlinear functional approximation [2], [3]. Modeling of microwave structures are typically regarded as a prediction (regression) task, which usually can be done by the ANN approach. However, the ANN modeling approach has its drawbacks, i.e., nonconvex quadric minimization may result in multiple minima, and it has the risk of over-fitting [4].

Recently, Vapnik's support vector machine (SVM) theory [5] has been successfully applied for classification and regression problems [6], [7]. Compared with the ANN approach, the SVM approach has several advantages: First, it solves a convex constrained quadratic optimization problem, whose error surface is free of local minima and has a unique global optimum. Second, it is based on the structural risk minimization (SRM) principle instead of empirical risk minimization, which is used in the ANN approach. The SRM principle implements trade-off well between the model's complexity and its generalization ability [8]. Furthermore, the SVM is based on small-sample statistical learning theory, whose optimum solution is based on limited samples instead of infinite samples. According to the above, the SVM regression is a promising approach that is superior to the traditional sampling approach.

To demonstrate the approach of SVM regression [commonly, SVM regression tasks called as support vector regression (SVR)], the electromagnetically trained-SVR (EM-SVR) approach is used to model LTCC 3-D vertical interconnect structure. The training data and testing data are obtained by a full-wave electromagnetic simulator (Ansoft HFSS). Experimental results suggest that the EM-SVR model has a better performance in predicting the microwave performance.

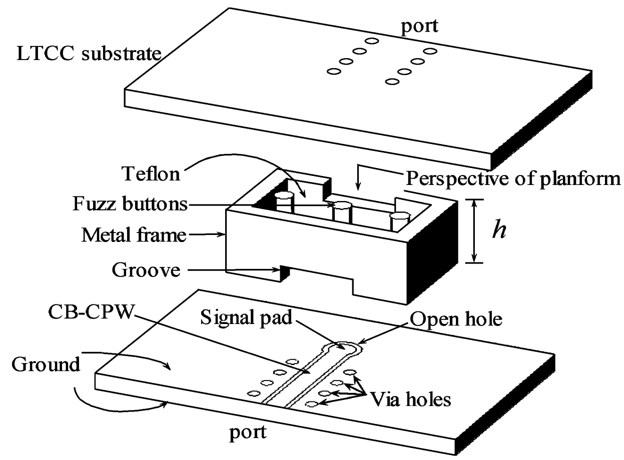


Fig. 1. Three-dimensional vertical interconnect structure.

## II. 3-D Vertical Interconnect Structure

The general face-to-face vertical interconnect structure is shown in Fig. 1. It is constructed by stacking two LTCC substrates with a rectangular metal fame sandwiched between them. The transmission line is conductor backed coplanar waveguide. Fig. 2 is the plane form of the structure (top view from the arrow in Fig. 1). Three fuzz buttons held together by a Teflon dielectric ($\varepsilon = 2.1$, $\tan\delta = 0.001$), which are embedded in the metal frame. Fuzz button is a kind of elastic column- form conductor with 0.5 mm diameter that is fabricated by randomly winded wire. It works well in severe vibration environments while maintaining a good connection and allowing easy rework. LTCC substrate fabricated using six-layer Ferro A6 ($\varepsilon_r = 5.7, \tan\delta = 0.002$) tape systems. Each fired single layer has the thickness of 0.1 mm. The coplanar waveguide has the line-width of 0.52 mm

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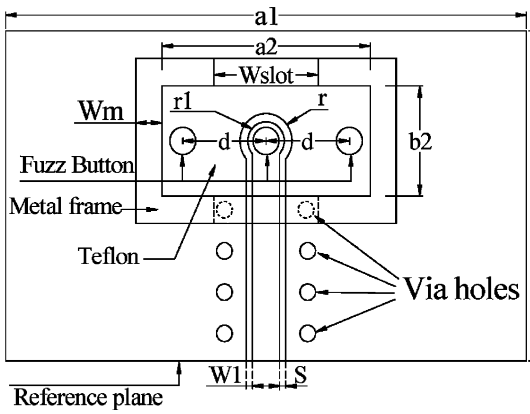


Fig. 2. Planform of vertical interconnect structure with $a1 = 10$ mm, $a2 = 4$ mm, $b1 = 6$ mm, $b2 = 2$ mm, $Wm = 0.5$ mm, $Wslot = 2$ mm, $W1 = 0.52$ mm, $S = 0.12$ mm, $r1 = 0.35$ mm. $r$ and $d$ are the model input variable parameters.

TABLE I
RANGE SELECTION OF SVR INPUT VARIABLES

| Input Parameters | Training Data | | | Testing Data | | |
|---|---|---|---|---|---|---|
| | Min | Max | Step | Min | Max | Step |
| $h$ (mm) | 2 | 3.5 | 0.5 | 2.25 | 3.25 | 0.5 |
| $d$ (mm) | 1.2 | 1.5 | 0.1 | 1.25 | 1.45 | 0.1 |
| $r$ (mm) | 0.5 | 0.9 | 0.1 | 0.55 | 0.85 | 0.1 |
| $f$ (GHz) | 1 | 16 | 1 | 1 | 16 | 0.5 |

and the gap of 0.12 mm to keep 50-$\Omega$ characteristic impedance. To eliminate unwanted parasitic modes, a grounding via array is used to connect the up-ground and down- ground. The metal frame has a groove with the height of 0.2 mm and the width $Wslot = 2$ mm to ensure the transmission of RF signal. The reference plane of the port and the physical layout parameters of the vertical interconnect are shown in Fig. 2.

## III. Support Vector Regression Model

Similar to the the ANN modeling approach, the SVR approach estimates the nonlinear function between a given input and its corresponding output in the training data acquired from EM simulation. This developed model can be used to predict outputs for given inputs which are not included in the training data.

For the vertical interconnect model, the amplitude of the return loss ($|S11|$) and insertion loss ($|S21|$) is the most important parameter. Therefore, $|S11|$ and the $|S21|$ are selected as the model output variables. The height of the metal frame ($h$, shown in Fig. 1), the radius of open holes ($r$) and the distance ($d$) between the fuzz buttons are used as the EM-SVR model input parameters. In addition, operation frequency is also included as an input parameter. The range of these input parameters is given in Table I, while the training and testing data are obtained by simulating in HFSS with these input variables separately.

The LIBSVM-Matlab code [9] is adopted to implement the SVR model. It computes a very efficient sequential minimal optimization (SMO) type decomposition method to solve the SVR problems. In the SVR approach, the proper kernel function needs to be selected, which is critical to the success of it.

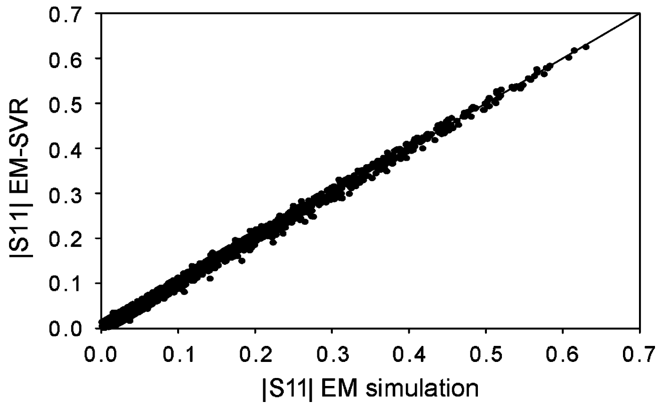


Fig. 3. EM simulation and EM-SVR computed $|S11|$ (training data).

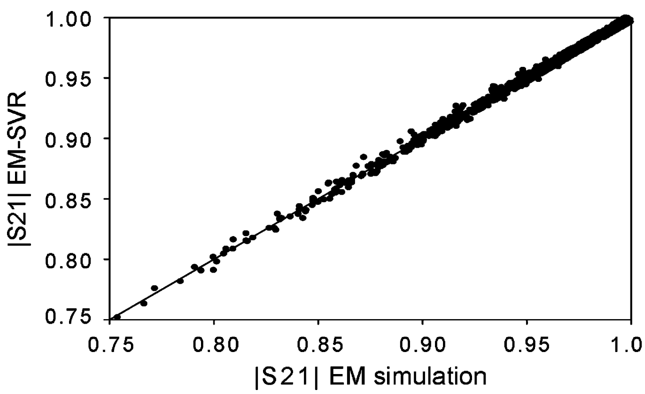


Fig. 4. EM simulation and EM-SVR computed $|S21|$ (training data).

Different kernel functions can change the prediction results remarkably. Some popular kernels are the linear kernel, polynomial kernels, and Gaussian radial basis function (RBF) kernels. Recently, a novel hybrid kernel has been proposed as well [10]. Here, LIBSVM provides four common kernels. The $v$-SVM regression based on radial basis function kernel function has been applied in this experiment. The radial basis function kernel nonlinear maps samples into a higher dimensional space, which has less numerical difficulties [11], and it can handle the case when the relation between target values and attributes is nonlinear. The linear kernel is a special case of radial basis function kernel. In addition, the polynomial kernel has more hyperparameters than the radial basis function kernel while the number of hyperparameters influences the complexity of model selection. The radial basis function kernel is shown as follows:

$$K(x, x_i) = \exp\left(-\gamma \cdot \|x - x_i\|^2\right) \tag{1}$$

$\gamma$ is a constant defining the kernel width. $x$ is the $n$-dimensional vector, and $x_i$ is the $i$th sample.

Before running the LIBSVM code, some SVR parameters need to be determined: the constant defining of kernel function ($\gamma$), tolerance of termination criterion ($\varepsilon$), the penalty parameter ($C$), and the constant $\nu$. $v \in [0, 1]$ is the parameter to control the number of support vectors. After performing several experimentations with different variable values, the variables are fixed as: $\varepsilon = 0.00001$, $v = 0.1$, $C = 500$, and $\gamma$ with the default

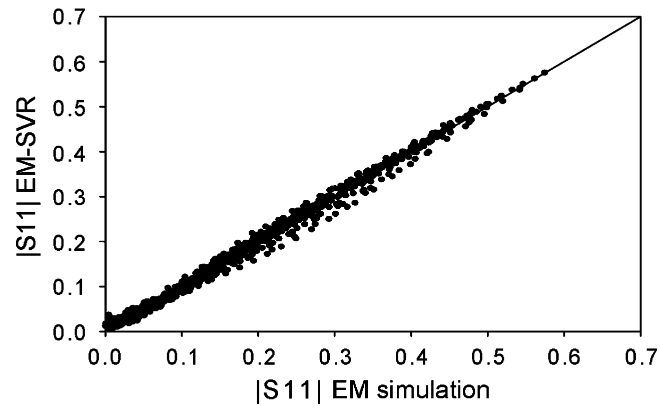


Fig. 5. EM simulation and EM-SVR computed $|S11|$ (testing data).

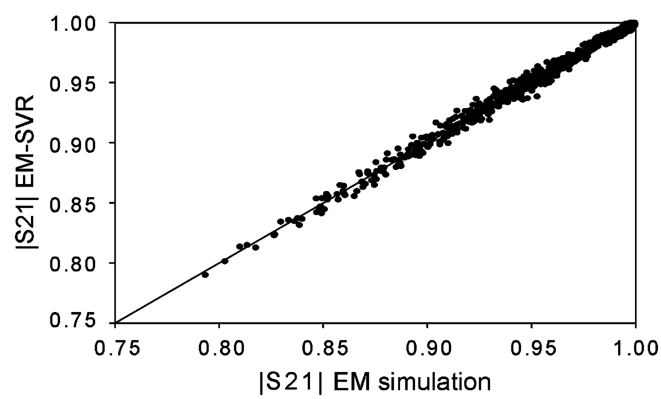


Fig. 6. EM simulation and EM-SVR computed $|S21|$ (testing data).

value: $\gamma = 1/k$, $k$ means the number of EM-SVR model input parameters.

Moreover, the quality of each model is evaluated as its prediction accuracy with mean squared error (MSE) and the correlation coefficient $(R)$ [12] as follows:

$$MSE = \frac{1}{N}\sum_{i=1}^{N}(y_i - x_i)^2 \tag{2}$$

$$R = \frac{\sum_{i=1}^{N}(x_i - \overline{x})(y_i - \overline{y})}{\sqrt{\sum_{i=1}^{N}(x_i - \overline{x})^2 \sum_{i=1}^{N}(y_i - \overline{y})^2}} \tag{3}$$

$x_i$ is the value of EM simulated $S$ parameters, and $y_i$ is the SVR predicted value, $N$ is the number of testing data. $\bar{x}$ is the EM simulated $S$-parameters samples mean value and $\overline{y}$ is the $v$-SVR predicted samples mean value.

The scatter plots of the EM-SVR model predicted $S$-parameter compared with the training data are shown in Figs. 3 and 4. The more the points are concentrated around the diagonal line, the better the predictions are. To illustrate the prediction ability, the predicted values by direct prediction are plotted against the EM simulation data in Figs. 5 and 6. Summary of MSE and $R$ are shown in Table II. As can be seen from the results, excellent agreement between the EM-SVR model and the EM simulation is achieved. Once the SVR model is fully developed, the computing time of the model is negligible compared to the full-wave EM simulator. In this example, the time required for the EM-SVR training is about 20.5 min. Testing the data takes about 0.375 s for 1116 samples (in Matlab), which means less than $3.4 \cdot 10^{-4}$ s per sample, whereas, HFSS uses about 10 min on the PC (with 2.8-GHz processor and a total RAM memory of 512 MB) for a single simulation. Consequently, the presented approach can acquire the same accuracy as the EM simulator with high computing efficiency.

TABLE II
CORRELATION AND ERROR RESULTS FOR THE EM-SVR MODEL

| Data | Training Data | | Testing Data | |
|---|---|---|---|---|
| $\|S\|$ | \|S11\| | \|S21\| | \|S11\| | \|S21\| |
| MSE | $7.943 \cdot 10^{-5}$ | $6.222 \cdot 10^{-6}$ | $1.041 \cdot 10^{-4}$ | $1.043 \cdot 10^{-5}$ |
| R | 0.9980 | 0.9982 | 0.9971 | 0.9963 |

## IV. CONCLUSION

A support vector machine regression approach has been presented in this letter. A practical 3-D vertical interconnect structure has been developed as an example. The experiment results confirm the excellent performance of this sampling method. It is shown that the developed model preserves the accuracy of the EM simulation and improves the computation efficiency. Once the EM-SVR model has been trained, it can be integrated into a CAD tool, for the analysis, design, and optimization of practical high density packaging structures.

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