Optimization of Microwave Circuit Parameters by CMA-ES Method

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Abstract: We propose a method to accurately estimate microwave circuit parameters from observed amplitude of reflection characteristics. Characteristics of analog circuits are often not optimal because of the errors in circuit parameters. We develop a novel method to accurately estimate the circuit parameter values using the covariance matrix adaptive evolution strategy (CMA-ES) and evaluate its performance in comparison with conventional methods.

Keywords: parameter estimation, microwave circuit, covariance matrix adaptation evolution strategy

Classification: Sensing

References

[1] A. Osseiran et al., “Scenarios for 5G mobile and wireless communications: the vision of the METIS project,” IEEE Communications Magazine, vol. 52, no. 5, pp. 26-35, May 2014. DOI: 10.1109/MCOM.2014.6815890
[2] T. Jing, H. YuNan and X. ZhiCai, “Optimization of analog circuit fault diagnosis parameters based on SVM and genetic algorithm,” Advances in information Sciences and Service Sciences, vol. 4, no. 4.6, pp.42-50, Mar. 2012. DOI: 10.4156/AISS.vol4.issue4.6
[3] S. Majumdar and H. Parthasarathy, “Wavelet-based transistor parameter estimation,” Circuits, Systems and Signal Processing, vol. 29, pp. 953-970, Oct. 2010. DOI: 10.1007/s00034-010-9181-9
[4] B. Apolloni et al., “Statistical parameter identification of analog integrated circuit reverse models,” Proc. Int. Conf. Artificial Neural Networks, pp. 449-458, Sep. 2009. DOI: 10.1007/978-3-642-04274-4_47
[5] L. Zhou, Y. Shi and Y. Li, “Soft fault diagnosis of analog circuit based on particle swarm optimization,” Journal of Electric science and Technology of Chinas, pp. 358-361, Dec. 2009. DOI: 10.1109/CAS-ICTD.2009.4960876
[6] N. Hansen and S. Kern, “Evaluating the CMA evolution strategy on multimodal test functions,” Parallel Problem Solving from Nature - PPSN VIII, pp. 282-291, Sep. 2004. DOI: 10.1007/978-3-540-30217-9_29
[7] J. A. Nelder and R. Mead, “A simplex method for function minimization,” Computer Journal, vol. 7, pp. 308-313, 1965. DOI:10.1093/comjnl/7.4.308
[8] K. Hayashi and K. Ichige, “Accurate estimation of analog circuit parameters by CMA-ES method,” Proc. International Symposium on Antenna and Propagation (ISAP), pp. 39-40, Jan. 2021.

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1 Introduction

Fifth-generation (5G) mobile communication technology has been attracted attention. Microwave circuits with high-precision are necessary to achieve high-performance high-speed mobile communication systems. However, the cost of actual fabrication is increasing as the circuit complexity increases [1]. Such circuit complexity may lead to the misdiagnosis of faults in analog circuits. Because it is impractical to accurately measure all the values of circuit parameters, the actual values of each parameter need to be estimated from the observed reflection characteristics of the entire circuit [2],[3].

Fault diagnosis has advanced together with computer science, and various fault diagnosis methods have been developed such as machine learning and analytic methods. However, analog circuit diagnostics still presents more problems than digital circuits diagnostics, such as increasing complexity of classifiers and heavy dependence on users’ priori knowledge [4],[5].

The covariance matrix adaptation evolution strategy (CMA-ES) is known as one of the best algorithms in black-box optimization [6]. It is widely used in various research fields such as optical device and drone systems, because of its superiority in problems with multimodality and inter-variable dependence. We believe that it will also work in analog circuit fault diagnosis.

In this paper, we propose a method to accurately estimate circuit parameters on the basis of the observed amplitude characteristics of reflection components using CMA-ES. The performance of the proposed method is evaluated through computer simulation.

2 Covariance Matrix Adaptation Evolution Strategy

CMA-ES is a method of evolutionary computation used in a real-valued continuous search space [6]. It is used to optimize black-box functions that return only output values for input parameters and whose derivatives are unknown. The generation of individuals at each iteration is controlled by the variance-covariance matrix $C$, the step size $\sigma$, and the mean vector $m$, and the optimal solution is derived sequentially as these are adapted with each iteration. In the following, generation of an arbitrary point $v$ in space in accordance with the normal distribution determined by the mean vector $r$ and variance $s^2$ is denoted as follows.

$$v \sim \mathcal{N}(r, s^2).$$  (1)

In each iteration of CMA-ES, the vector $y_k$ is first generated from the multivariate normal distribution represented by $C$, where $k$ is the $k$th generated in that iteration, and $\lambda$ is the number of candidate solutions generated in one iteration. The map $x_k$, obtained by multiplying $y_k$ by $\sigma$ and adding the
mean vector \( \mathbf{m} \), is the input vector of each candidate solution.

\[ y_k \sim \mathcal{N}(0, C), \]  
\[ x_k = \mathbf{m} + \sigma y_k. \]

After the degree of adaptation \( u(\mathbf{x}_k) \) is calculated for each candidate solution, the mean vector \( \mathbf{m} \) is updated. The input vectors \( \mathbf{x}_k \) are ranked on the basis of the value of \( u(\mathbf{x}_k) \), and the top \( \mu = \lfloor \lambda/2 \rfloor \) solutions among them are used. Each is multiplied by a weight coefficient \( w_i \) in accordance with the rank, and the sum of the multiplied solutions is the new mean vector \( \mathbf{m}' \), where \( i \) means the rank.

\[ \mathbf{m}' \leftarrow \sum_{i=1}^{\mu} w_i \mathbf{x}_i. \]

Finally, update the step size \( \sigma \) and the covariance matrix \( \mathbf{C} \), where \( \mathbf{p}_\sigma \) and \( \mathbf{p}_C \) are the evolutionary paths of \( \sigma \) and \( \mathbf{C} \), respectively.

\[ \sigma' \leftarrow \sigma \star \exp \left( \frac{c_\sigma}{d_\sigma} \left( \frac{\|\mathbf{p}_\sigma\|}{E\|N(\emptyset, I)\|} - 1 \right) \right) \]  
\[ \mathbf{C}' \leftarrow f_c \mathbf{C} + c_1 \mathbf{p}_C \mathbf{p}_C^T + c_\mu \sum_{i=0}^{\mu} w_i y_i y_i^T. \]

Here, \( c_\sigma \) is the learning rate of the evolutionary path, \( c_1 \) and \( c_\mu \) are the learning rates of \( \mathbf{C} \), and \( d_\sigma \) is the decay parameter of \( \sigma \). \( f_c \) is a function that has \( \mathbf{p}_\sigma \) and learning rate as variables and is responsible for the decay of \( \mathbf{C} \). By repeating the above procedure, the multivariate normal distribution will converge to the Dirac delta distribution at vector \( \mathbf{x}^* \), which is the optimal solution.

### 3 Proposed method

We propose a method to estimate the values of circuit parameters from the characteristics of the entire analog circuit using CMA-ES. First, we set an optimization problem and describe the application of CMA-ES to it.

#### 3.1 Setting up optimization problem

In microwave circuits, some input signals are not transmitted to the output port and are reflected to the input port. The ratio of the incident wave to the reflected wave is called the return loss \( S_{11} \) and is designed to be small only at a desired frequency in circuits such as microwave filters. We generally can observe the amplitude of the return loss characteristics given by

\[ |S_{11}| \text{ [dB]} = 20 \log_{10} \left| \frac{Z_{\text{in}} - Z_0}{Z_{\text{in}} + Z_0} \right|, \]

where \( Z_0 \) is the characteristic impedance and \( Z_{\text{in}} \) is the input impedance when the output terminal is terminated at \( Z_0 \). Since the return loss has impedances as variables, the return loss of high-frequency LC circuits becomes frequency dependent.

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On the basis of the theory of least squares method, the problem of parameter estimation is replaced by the problem of minimizing the root mean squared error (RMSE) between the return loss in the fault circuit and that in the computational model. When the range of angular frequency $\omega$ is $\omega_1 \leq \omega < \omega_2$, the sampling frequency is $\Delta \omega$, and $N$ points are measured, the problem of minimizing the objective function $h(\theta)$ for the estimated vector $\theta$ can be expressed as

$$\min_{\theta} h(\theta) = \frac{1}{\omega_2 - \omega_1} \int_{\omega_1}^{\omega_2} |f(\omega) - g(\theta, \omega)|^2 d\omega$$

$$= \sqrt{\frac{1}{N} \sum_{n=0}^{N-1} |q_n - g(\theta, \omega_1 + n\Delta \omega)|^2}. \quad (8)$$

where $f$ is the measurement curve, $g$ is the model function for the parameter $\theta$, and $q_n$ is the $n$-th discrete measurement. Note that we can apply the method to $S_{21}$ as well as $S_{11}$, and indeed better estimation performance could be observed. We use only $S_{11}$ in this study because the characteristics we can measure are often limited in actual situation.

### 3.2 Application of CMA-ES

We optimize the problem discussed in the previous section by using CMA-ES. Noting that the scale of each element generally differs greatly, the input parameter $x_k$ of a candidate solution in CMA-ES was set as the ratio to the design value of each element. Therefore, the estimated parameter vector for the least squares method, $\theta_k$, is a $t$-dimensional vector where each dimension of $x_k$ is multiplied by the design value of the corresponding element $E_\ell$.

$$\theta_k = [E_1 x_{k1}, E_2 x_{k2}, \ldots, E_\ell x_{k\ell}, \ldots, E_t x_{kt}]^T. \quad (9)$$

The return loss is obtained from the parameter’s values corresponding to the candidate solution and compared with the actual return loss at each frequency. The RMSE between the return losses is treated as the fitness of the candidate solutions.

$$u(x_k) = h(\theta_k). \quad (10)$$

The termination condition is when the number of iterations exceeds a threshold $T$ or when the step size $\sigma$ is less than the specified value $\epsilon$. The parameter’s values corresponding to the best solution were taken as the estimate.

### 4 Simulation

#### 4.1 Simulation Specifications

We evaluated the estimation accuracy of the proposed method using LTSpice in comparison with some conventional methods. The gradient descent is frequently used in many optimization problems and we used it as a benchmark. The Nelder-Mead method was used for comparison because it holds multiple solution candidates like CMA-ES, and was considered to work effectively in
fault diagnosis problem. The multi-peak bandpass filter circuit in Fig. 1(a), which resonates at 33.8 and 65.8 MHz as in Fig. 1(b), was used for evaluation. We prepared two fault states; one where the deviation of either $+5\%$ or $-5\%$ was added to the circuit parameters as a mild fault, and the other of either $+20\%$ or $-20\%$ deviation as a severe fault.

Note that the passband frequencies are not in 5G or sub-6G band due of a basic trial purpose, however we can adjust the frequency range into 5G or sub-6G bands by simply changing the frequency range or order. The optimization process works in a similar manner.

The estimation starts from the return loss curve at the design value. The model return loss curve should preferably overlap with the actual curve for each failure state eventually. As the model curve approaches the actual curve, the estimated value of each parameter is expected to move from the design value to the actual value.

### 4.2 Estimation Accuracy Evaluation

Figure 2 shows the behavior of RMSE in each iteration of parameter estimation. The estimated values for each parameter in each simulation are shown
Fig. 2. Behavior of RMSE as a function of the number of iteration.

The results in Fig. 2 show that the proposed method outperforms the other methods at minimizing the RMSE. This corresponds to the results in Table I, which show that the proposed method is more accurate than the other methods. In addition, the gradient descent did not minimize the RMSE very well, which suggests that the objective function is multimodal and falls into a local solution. This is also important for the Nelder-Mead method, which may affect the polyhedral change when the vertices of the polyhedron fall into local solutions.

Table I shows the estimated values of the circuit parameters after 330 iterations. We see from Table I that the estimation in the severe failure state fell into a local solution. On the other hand, the proposed method did not fall into local solutions, because CMA-ES does not use the objective function for adaptation, select candidate solutions sequentially, or retain the solution set. Therefore, even if a candidate solution falls into a local solution as in other methods, a new solution set is generated in the next iteration, and it is tolerant of local solutions if the step size is large enough in relation to the solution space. Through this simulation, the optimal solution was obtained in spite of the multimodality, and highly accurate estimation was achieved.
Table I. Comparison of the ideal and estimated values.

(a) Mild fault estimation.

| Element | Initial value | True value | Gradient | Nelder-Mead | Proposed |
|---------|---------------|------------|----------|-------------|----------|
| $C_1$   | 10 pF         | 10.5 pF    | 10.5 pF  | 10.4 pF     | 10.5 pF  |
| $C_2$   | 1.0 pF        | 0.950 pF   | 1.01 pF  | 0.949 pF    | 0.950 pF |
| $C_3$   | 25 pF         | 26.25 pF   | 25.85 pF | 26.24 pF    | 26.25 pF |
| $C_4$   | 1.0 pF        | 0.950 pF   | 0.999 pF | 0.977 pF    | 0.950 pF |
| $L_1$   | 1.0 $\mu$H    | 1.05 $\mu$H| 1.04 $\mu$H| 1.05 $\mu$H| 1.05 $\mu$H|
| $L_2$   | 0.50 $\mu$H   | 0.525 $\mu$H| 0.549 $\mu$H| 0.525 $\mu$H| 0.525 $\mu$H|
| $L_3$   | 1.0 $\mu$H    | 0.950 $\mu$H| 0.998 $\mu$H| 0.923 $\mu$H| 0.950 $\mu$H|

(b) Severe fault estimation.

| Element | Initial value | True value | Gradient | Nelder-Mead | Proposed |
|---------|---------------|------------|----------|-------------|----------|
| $C_1$   | 10 pF         | 12.0 pF    | 8.67 pF  | 11.9 pF     | 12.0 pF  |
| $C_2$   | 1.0 pF        | 1.20 pF    | 1.07 pF  | 1.19 pF     | 1.20 pF  |
| $C_3$   | 25 pF         | 20.00 pF   | 24.88 pF | 19.98 pF    | 20.00 pF |
| $C_4$   | 1.0 pF        | 1.20 pF    | 1.00 pF  | 0.970 pF    | 1.20 pF  |
| $L_1$   | 1.0 $\mu$H    | 0.800 $\mu$H| 0.847 $\mu$H| 0.800 $\mu$H| 0.800 $\mu$H|
| $L_2$   | 0.50 $\mu$H   | 0.600 $\mu$H| 0.644 $\mu$H| 0.600 $\mu$H| 0.600 $\mu$H|
| $L_3$   | 1.0 $\mu$H    | 0.800 $\mu$H| 0.999 $\mu$H| 0.860 $\mu$H| 0.800 $\mu$H|

by using the least squares method and CMA-ES.

Note that it is common in actual microwave circuits that chip components contain parasitic elements and transmission lines suffer from frequency dispersion. Those components can often be replaced by equivalent circuits, and frequency-dependent elements can adequately be estimated by the optimization in each frequency subband.

5 Concluding Remarks

We proposed a method to accurately estimate circuit parameters’ values from the characteristics of the entire analog circuit using the covariance matrix adaptive evolution strategy (CMA-ES). For the problem of RMSE minimization, the proposed method outperforms the other methods in terms of both of the convergence speed and the optimized characteristics. We focused only on the fundamental circuit simulations in this letter, and will try to see the effect of external interferences when we apply the proposed optimization method to actual microwave circuits. Also we should evaluate and improve the estimation accuracy in such a situation, they remain as some of our future works.

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