Bayesian Optimization of High-Speed Channel for Signal Integrity Analysis

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***Abstract*— As technology advanced, the demand for data bandwidth has been increasing. To meet this demand, the data rate of the channel has been increased, which causes a lot of signal integrity problems. Optimization of the channel is important to solve these problems. Channels are usually optimized with the empirical knowledge of signal integrity designers. However, it is not accurate and requires numerous iterations. On the other hand, a Bayesian optimization method can quickly find optimized parameter values without relying on empirical knowledge. Therefore, this paper proposes a method for optimizing high-speed channel using Bayesian optimization. The proposed method optimizes the frequency response result such as insertion loss, and find the optimal physical dimension parameters. Finally, the optimized results of the proposed method were verified by comparing all the simulation results in the range of the channel.**

Keywords*— *Bayesian optimization, high-speed channel, signal integrity (SI)

I. INTRODUCTION

Recently, the demand for data bandwidth has been increasing due to the development of artificial intelligence. To meet this demand, it is necessary to increase the data rate or the number of the Input/Output (I/O) channels. However, the increase of the data rate or the I/O channels causes signal integrity problems [1]-[2]. In order to solve the signal integrity problem of the channels, the channels should be optimized. Optimizing the physical dimensions of the channel is usually done with the empirical knowledge of the signal integrity designer and it is a time-consuming process because it is done through numerous iterations. Therefore, a way to optimize the channel without relying on the experience of the signal integrity designer is essential.

Various methods of optimizing the high-speed channel without relying on the experience of the designers have been studied. The RLGC parameters of the channel can be predicted according to the channel dimension through the Artificial Neural Network (ANN) and the parameters are optimized using Genetic Algorithm (GA) [3]. However, this method can only be used after obtaining several RLGC values using the Electromagnetic (EM) simulation. This is time-consuming and requires more data to get more accurate results, which will increase the time required.

In this paper, we propose a method that can optimize high-speed channel using Bayesian optimization based on the analytic model. Bayesian optimization can easily and accurately find optimal values for results even when multiple parameters are present. The analytic model of a channel that has many parameters can be optimized using Bayesian optimization. Since many models of channels already exist [4] and they are actually used in pre-simulation, it is necessary to optimize them using given models. When optimizing the channel, it should be optimized based on the frequency response of the models. Using circuit simulation tools makes it difficult to use the results directly as input to the optimization algorithm. However, when the circuit simulation based on Python is used instead of the circuit simulation tool, the result data is obtained and this value is used directly to reduce time and automation. Among the Bayesian optimization methods, the Gaussian Process (GP) method and the Tree-structured Parzen Estimator (TPE) method were used for the optimal design of the channel. A model of one microstrip line was used as an example of the optimization method.

II. BAYESIAN OPTIMIZATION

Bayesian optimization aims at finding an optimal solution x^* that maximizes the function value $f(x)$ by assuming an unknown objective function f that receives an input value x.

$$x^* = \underset{x \in X}{\operatorname{argmax}} f(x) \tag{1}$$

It is also a way to optimize hyperparameters in machine learning [5]. As well as finding the hyperparameters, it can be effectively used even in finding the optimum value of some model. The Bayesian optimization is an optimization methodology that can be considered to carry out the whole search process more systematically while sufficiently reflecting prior knowledge when conducting research on new model values every time. The Bayesian optimization makes it easy and accurate to find optimal values even when multiple parameters exist. The Bayesian optimization requires an acquisition function and a surrogate model.

The acquisition function is a function that recommends the next input x_{t+1} value candidate based on the probabilistic estimation results of the objective function to date. The selected x_{t+1} is the most useful value for finding the optimal input x^* of the objective function. In this paper, Expected Improvement (EI) is used as the acquisition function. The EI function is designed to implicitly include both exploration and exploitation strategies and it worked well in variety model. The EI defined as:

$$EI_{y^*}(x) = \int_{-\infty}^{y^*} (y^* - y, 0) p(y|x) dy \tag{2}$$

where y^* is a threshold value of the objective function, x is the proposed set of model parameters, y is the actual value of the objective function using x, and $p(y|x)$ is the surrogate probability model representing the probability of y given x.

The surrogate model is a model that performs a probabilistic estimation of the shape of an unknown objective function based on the investigated points. The surrogate model should cover the uncertainty of the objective function estimation based on the investigated points. The Gaussian process(GP) is mainly used, but the Tree-structured Parzen Estimator (TPE) is also used for the surrogate model [6].

A. Gaussian Process (GP)

The Gaussian Process(GP) has been used for a long time as a method of model-based optimization. GP is a probabilistic model for representing the probability distribution of some functions different from the ordinary probability model, and the joint distribution between the components is characterized by following the Gaussian distribution. GP expresses the probability distribution for the functions using the mean function μ and the kernel function (covariance function) K:

$$f(x) \sim GP(\mu, K) \tag{3}$$

The choice of kernel function K can have a significant impact on the quality of the surrogate model. The Automatic Relevance Determination (ARD) kernel is a common variation. This kernel define important quantities needed to compute the predictive distribution, including

$$k(x) = \left(K(x, x_1) \cdots K(x, x_i)\right)^T \tag{4}$$

$$\mathrm{K}_{\mathrm{j,k}} = K(x_j, x_k) \tag{5}$$

Predictions follow a normal distribution, therefore we know $\mathrm{p(y \mid x) = N(y \mid \hat{\mu}, \sigma^2)}$ where, assuming $\mu(x) = 0$,

$$\hat{\mu} = k(x)^T (K + \sigma_n^2 \mathrm{I})^{-1} \mathrm{y} \tag{6}$$

$$\hat{\sigma}^2 = K(x, x) - k(x)^T (K + \sigma_n^2 I)^{-1} k(x) \tag{7}$$

where k(x) is as in (4), and K is given by (5).

B. Tree-structured Parzen Estimator (TPE)

The Tree-structured Parzen Estimator (TPE) applies the Bayes rules to create the model. Instead of expressing $p(y|x)$ directly, use:

$$p(y|x) = \frac{p(x|y) * p(y)}{p(x)} \tag{8}$$

The score of the objective function is given by the probability of a given $p(x|y)$. The TPE defines $p(x|y)$ using two such densities:

$$p(x|y) = \begin{cases} \ell(x) & \text{if } y < y^* \\ g(x) & \text{if } y \geq y^* \end{cases} \tag{9}$$

where $\ell(x)$ represents a lower value of the objective function than the threshold, $g(x)$ represents a higher value of the objective function than the threshold.

III. Proposal of Bayesian Optimization of High-Speed Channel

Fig. 1. shows the flow chart of the proposed optimization method. The proposed method is to optimize the frequency response of the channel using Bayesian optimization to find the optimum dimension value of the channel. First, the target channel and the target parameters to be optimized must be defined. There are two types of parameter. One is the physical dimensions of the channel, such as the trace width, space, and dielectric height. The other is material property such as dielectric constant and loss tangent. Target parameter ranges must be defined. Optimization algorithms can be used to determine the optimal value of a parameter within that range.

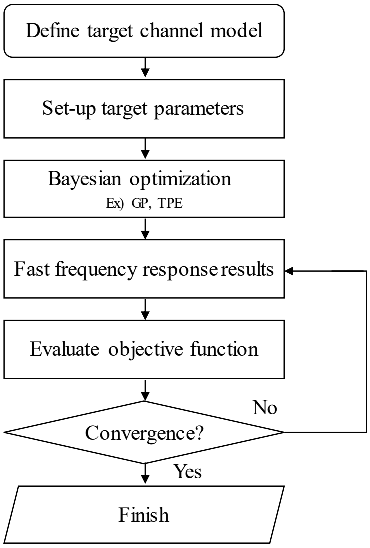


Fig. 1. Flow chart of the proposed optimization method

After defining the target parameters and the range of the parameters, the optimization algorithm needs to be selected. The optimization algorithms include not only basic methods such as random search, manual search, and grid search, but also Bayesian optimization methods such as Gaussian processes (GP) and Tree-structured Parzen Estimators (TPE). The proposed method with Bayesian optimization shows the most optimized results when various parameters are present.

Then, the frequency response results should be obtained. However, obtaining frequency response results using a simulation tool is time-consuming and requires manual input. Therefore, Python, a language that uses optimization algorithms, and Pyspice, a spice simulation library available in Python, can be used to obtain frequency response results and optimize them using Bayesian optimization methods at the same time. And the objective function should be evaluated. Its objective function is as follows:

$$f(x) = \left(y - y_{target}\right)^2 \tag{10}$$

where y denotes frequency response results which obtain using the design parameters, y_{target} denotes the target specification of the target channel. The objective function is evaluated and the process of obtaining the frequency response result is repeated while changing the dimension of the channel until it converges. When the objective function converges and finds the optimal value, it is finished.

IV. Verification of the Proposed Method

The high-speed channel and design parameters for verification are shown in Fig. 2. The target channel is a single-line microstrip channel. The parameters are trace width, trace thickness, dielectric height, and dielectric constant. The range of the input parameters are shown in Table I. Transmission line modeling (TLM) method is used to model the microstrip line [4]. The optimization algorithm uses the Gaussian process (GP) and the Tree-structured Parzen Estimator (TPE)

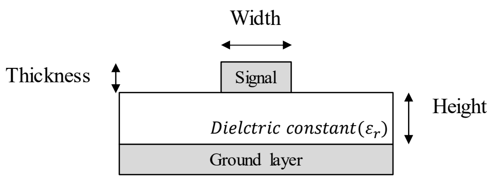
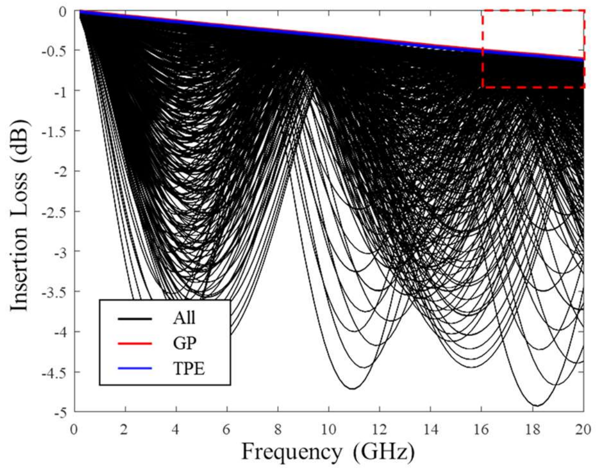


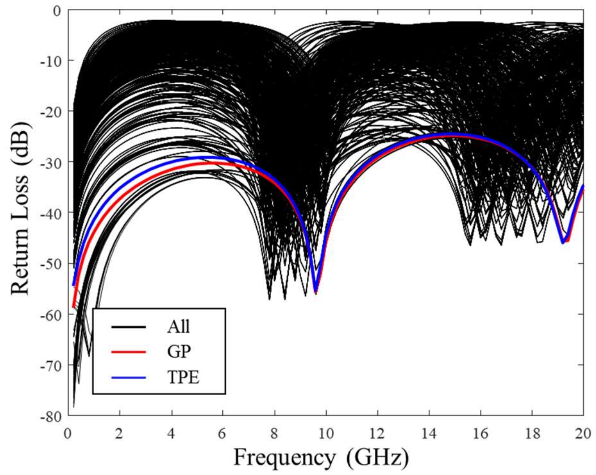
Fig. 2. Target channel and target parameters for Bayesian optimization

TABLE I. RANGE OF PARAMETERS OF THE CHANNEL

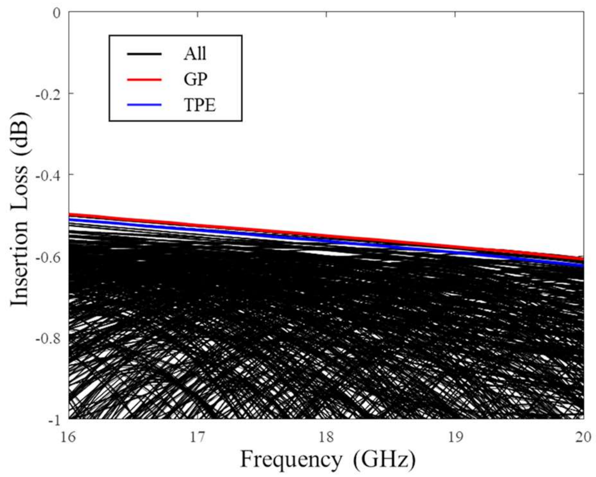
Parameter	***Min***	***Max***
Width	0.1 mm	0.8 mm
Thickness	0.01 mm	0.05 mm
Height	0.1 mm	0.8 mm
Dielectric constant	3	5



(a)



(b)



(c)

Fig. 3. Verification of channel optimization result by Bayesian optimization. (a) insertion loss, (b) return loss, (c) insertion loss in Red dotted part in (a)

described in chapter 2. The insertion loss is used for optimization as frequency response results. The optimized parameter values of the channel using the proposed method are shown in Table II.

TABLE II. OPTIMIZED DESIGN PARAMETERS USING THE PROPOSED METHOD

Algorithm	***Width***	***Thickness***	***Height***	ε_r
Bayesian - GP	0.797	0.0408	0.323	3.001
Bayesian - TPE	0.756	0.0199	0.286	3.006

In Fig 3.(a) shows the insertion loss result of the channel and (b) shows the return loss result of the channel. The black curves are the S-parameter results when all values within each parameter range are simulated by the circuit simulation tool. The red line is the S-parameter result of the GP method in the Bayesian optimization methods. The blue line is the S-parameter result of the TPE method in the Bayesian optimization methods. For more detail, only the 16-20GHz band of insertion loss is enlarged and shown in Fig 3. (c). Although the optimal design parameter values of the parameters were a little different, both GP and TPE methods found optimal design parameters with optimal insertion loss. Comparing the two methods, the GP method found the most optimized result.

V. CONCLUSION

In this paper, Bayesian optimization of the high-speed channel for signal integrity analysis was proposed. Given the target channel and its analytic model, the proposed method can quickly obtain optimized dimension values for the channel because the 3D EM simulation tool and circuit simulation tool are not used and proposed optimization is implemented only with Python. Finally, the proposed Bayesian optimization finds not only optimal insertion loss results for the channel but also optimal design parameter values at that time. Both GP and TPE methods have found optimal results, but when comparing the two proposed Bayesian optimization methods, the results of GP are more accurate. The proposed method can find the optimized value for a more complex channel if the analytic model exists.

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