S-parameter Modeling and Optimization using Deep Gaussian Processes

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***Abstract*—In this work, a new methodology based on deep Gaussian processes (DGP) is proposed for the modeling and optimization of the S-parameter response of a microwave device. The DGP is used as a surrogate model to directly predict the magnitude (or phase) of the S-parameter as a function over the frequency and over the design parameters of the device. Subsequently an *objective probability distribution* is retrieved and maximized in a Bayesian optimization (BO) scheme. The new strategy overcomes the limitation of the standard Bayesian optimization that employs an objective function model: simple objective functions are easy to model but may lead to sub-optimal responses, while complicated objective functions may require more powerful and less efficient models. An adequate microwave example demonstrates the increased optimization accuracy of the proposed approach, comparing to standard BO.**

***Index Terms*—S-parameter, electronic design automation (EDA), Bayesian optimization, deep Gaussian processes (DGP).**

I. Introduction

In microwave design, many expensive simulations are often executed to find the design parameter that produce the desired S-parameter response. Thankfully, this task can be automated and accelerated using optimization algorithms, that are able to identify the optimal parameter values with a reduced number of simulations [1]. In the last decades, efficient optimization strategies have been built on surrogate models that replace the simulator by representing the device response as a function of design parameters. In particular, the Bayesian optimization (BO) [2], [3] employs a stochastic surrogate model, such as the Gaussian process (GP) [4], that is updated sequentially, as soon as each new simulation is completed. In fact, the stochastic model predicts the likelihood for any parameter values to yield the desired performance. Consequently, the design parameters that maximize such likelihood can be sequentially selected for the next simulations, until the best are found.

In standard BO, the performance of the S-parameter response is measured and optimized via a user-defined *objective function* over the design parameters space. However, if the objective function is too simple, the surrogate may fail to identify the best design parameters combination. On the other hand, complicated objectives may require less data-efficient surrogate models. In this work, a new methodology is proposed to overcome this limitation by directly model the S-parameter response, rather than an objective function, using deep Gaussian processes (DGP) [5]. In fact, DGPs are composed by an input-output chain of Gaussian processes (Fig.1a): the resulting architecture is able to represent more complicated functions, and functions that are a realization of nonstationary stochastic processes. Subsequently, a suitable objective probability distribution can be retrieved from the DGP and then maximized, in order to built a more efficient Bayesian optimization scheme.

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II. Methodology

The proposed S-parameter optimization strategy based on deep Gaussian process is represented in Fig.1b. The strategy begins by training the DGP surrogate model on few initial samples of a scalar S-parameter response s:

$$s(\boldsymbol{p}, f) \sim DGP(\boldsymbol{p}, f) \qquad (1)$$

where $\boldsymbol{p}$ is the design parameters vector and f is the frequency. Next, an *objective probability distribution* $\hat{q}$ is defined as follows, based on the design requirement of the microwave device:

$$\hat{q}(\boldsymbol{p}) = \sum_{f \in T_f} g(DGP(\boldsymbol{p}, f), f) \qquad (2)$$

where T_f is a test set of frequencies, while the g function is linear over the s values predicted by the DGP. The design specifications can be incorporated in g such that better S response return higher values of the function. Since the s values are modelled by the DGP as random Gaussian variables, the linearity of g guarantees that the $\hat{q}$ values also obey to a Gaussian distribution. Thus, the analytical form of the expectation and the variance of the objective distribution is known, for each possible design parameter values $\boldsymbol{p}$. Consequently, similar to the standard Bayesian optimization [2], [3], an acquisition function can be computed on $\hat{q}$ to select the design parameters that are most likely to maximize the objective distribution. Finally, the new S response relative to selected parameters is simulated and added to the initial samples, in order to update the surrogate model. This process is re-iterated until a stop

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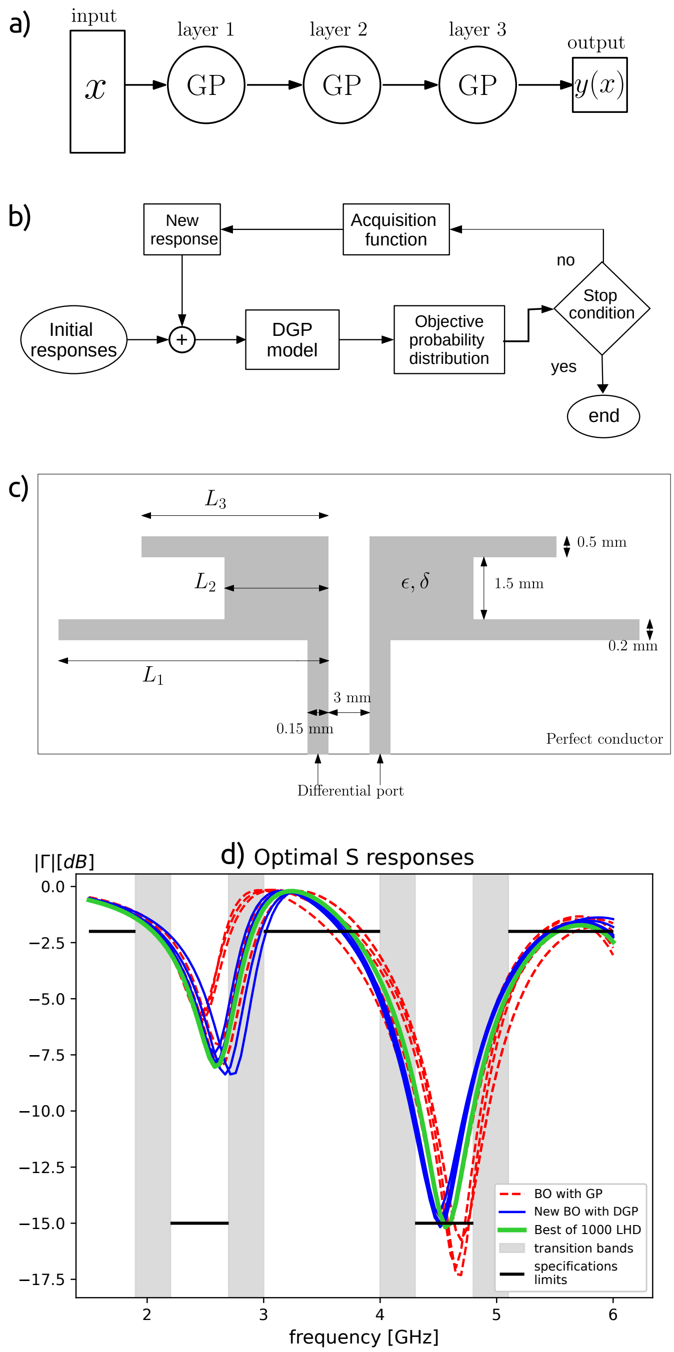

Fig. 1. a) Example of deep Gaussian process architecture. b) Workflow of the proposed strategy based on a DGP model of the S response over the frequency. c) Dual-band slot antenna (top view); the geometry is symmetric with respect to the vertical axis. d) Optimal S-responses identified with 5 different runs of the new strategy and the standard BO, after 30 iterations.

condition is met. As a result, the new strategy aims at the parameter values that produce the highest objective distribution expectation, which corresponds to the best S response for the considered design specifications.

III. Application Example

The presented strategy is used to optimize the magnitude of the Γ reflection coefficient of a dual-band slot antenna [6] in the range $[1, 4.5]$ GHz, relative to the design parameters L_1, L_2, L_3 (Fig.1c). The reflection scattering coefficient Γ of the DUT is computed at the single differential port via ADS Momentum [7] for 50 equispaced frequencies in $[1.5, 6]$ GHz. Then, the g function for the objective distribution is defined as the absolute distance between the response and the desired specification limits for the pass bands and the stop bands:

$$g(\boldsymbol{p}, f) = |\Gamma(\boldsymbol{p}, f)| - 0.79 \qquad \text{for } f < 1.9\,\text{GHz} \tag{3a}$$
$$g(\boldsymbol{p}, f) = 0.18 - |\Gamma(\boldsymbol{p}, f)| \qquad \text{for } f \in [2.2, 2.7]\,\text{GHz} \tag{3b}$$
$$g(\boldsymbol{p}, f) = |\Gamma(\boldsymbol{p}, f)| - 0.79 \qquad \text{for } f \in [3.0, 4.0]\,\text{GHz} \tag{3c}$$
$$g(\boldsymbol{p}, f) = 0.18 - |\Gamma(\boldsymbol{p}, f)| \qquad \text{for } f \in [4.3, 4.8]\,\text{GHz} \tag{3d}$$
$$g(\boldsymbol{p}, f) = |\Gamma(\boldsymbol{p}, f)| - 0.79 \qquad \text{for } f > 5.1\,\text{GHz} \tag{3e}$$

Next, a 3-layer DGP model is used in the proposed strategy (Fig.1a). Both the new strategy and the standard BO with GP are executed for 30 iterations, for 5 different sets of initial response samples. Each set contains S responses simulated for 10 design parameters combination in a latin hypercube design [8]. For reference, a baseline optimal response is found among 1000 simulations with different parameter values, selected from a latin hypercube design. Figure 1d shows that, for each of the 5 initial sets, the new strategy using DGP and objective distribution identifies an optimal response Γ (blue curves) that is closer to the reference optimal response (green curve), comparing to the standard BO with objective function modeling via GP (red curves). Moreover, experiments indicate that a simple GP could not be used reliably as surrogates in the new strategy, since they are not sufficiently powerful to model the S parameter curves over the frequency.

The use of DGP increases the computational time needed to perform each iteration of the optimization. In fact, due to the use of variational inference at each layer, the DGP requires around 20 sec to be trained in this application example, compared to 1 sec using a simple GP. Similarly, inferring the objective values (Equation 2) for the acquisition function takes around 7 sec with DGP, versus 1 sec with GP.

IV. Conclusion

The presented Bayesian optimization strategy allows to directly model an S-parameter curve over frequency using a deep Gaussian process (DGP). A new objective probability distribution can be computed on the model in order to value any S-parameter curve according to sophisticated design specifications. Similar to standard Bayesian optimization, new S-parameter responses can be sequentially collected, improving the model along the way. The new strategy better identifies good S-parameter responses with a low amount of expensive simulations, compared to standard BO.

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