AN EFFICIENT MULTI-FIDELITY BAYESIAN OPTIMIZATION METHOD FOR ELECTROMAGNETIC METASURFACE ABSORBER DESIGN

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Abstract

To tackle the challenges of nonlinearity, multimodality, and computational intensity in optimizing an electromagnetic (EM) metasurface (MS) absorber for radio frequency energy harvesting (RFEH), we propose a multi-fidelity Bayesian optimization (BO) method. By integrating a multi-path lower confidence bound (LCB) prescreening and an adaptive sample-replacement strategy, the proposed BO method ensures robust exploration and efficient design, avoiding premature convergence and maintaining compact training datasets. Benchmark test results confirm its high accuracy and fast convergence, while practical applications demonstrate substantial improvements in accuracy and efficiency in RFEH MS absorber design.

1 Introduction

The increasing demand for low-power electronics has made traditional battery-powered devices unsustainable due to high maintenance and replacement costs. Radio frequency (RF) energy harvesting (RFEH) offers a promising alternative, yet its design faces challenges such as low power density, scattered spectrum, and wave variability. Electromagnetic (EM) metasurface (MS) absorber has emerged as a competitive candidate for RFEH systems, but designing an MS absorber requires compromising conflicting demands for high efficiency, broadband operation, and compactness. Consequently, the design of an EM-MS is a computationally intensive, nonlinear optimization problem.

Although effective, traditional metaheuristic algorithms are often too resource-intensive for RFEH MS. Bayesian optimization (BO) offers a more efficient approach by employing surrogate models, and a multi-fidelity BO further enhances the solution efficiency by combining fast low-fidelity (LF) data with accurate high-fidelity (HF) simulations. However, existing BO methods struggle with middle- and high-dimensional, multimodal problems. To solve the aforementioned challenges, this paper proposes a multi-fidelity BO method that integrates nonlinear Gaussian Process Regression (NAGPR), a multi-path lower confidence bound (LCB) strategy, and an innovative adaptive sample-replacement approach.

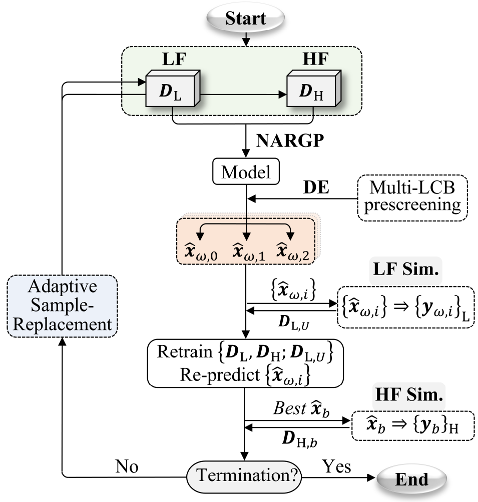

Fig. 1: The general iterative procedures of the proposed BO method.

2 The proposed Bayesian optimization method

The iterative process of the proposed BO method is shown in Fig. 1. It starts by constructing initial datasets D_L and D_H, with N_L LF samples and N_H HF samples ($N_H < N_L$) generated via Latin hypercube sampling. A surrogate model using the NARGP is then built to represent the design space. Three promising candidates ($x_{\omega,0}$, $x_{\omega,1}$, $x_{\omega,2}$) are identified using a multi-LCB prescreening strategy, where the surrogate model is optimized using the differential evolution (DE) algorithm with the following acquisition function: $LCB(x) = \hat{\mu}_*(x) - \omega \cdot \hat{\sigma}_*(x)$, where $\hat{\mu}_*(x)$ and $\hat{\sigma}_*(x)$ represent the predicted mean and standard deviation of the objective at point x, with $\omega = [1, 2, \ldots, M_{\max}]$ as multi-LCB constants. The three potential optima undergo LF simulations. The NARGP model is then updated, and the candidates are repredicted. The best HF prediction is evaluated via HF simulations. If the maximum iteration number is reached, the best HF value is returned; otherwise, an adaptive sample-replacement strategy is applied, and the procedure continues.

The adaptive sample-replacement strategy (Fig. 2) is a pivotal innovation in the proposed method, balancing computational efficiency and sampling density near the optimal solution. From the candidate pool generated by multi-LCB prescreening, M promising LF samples are

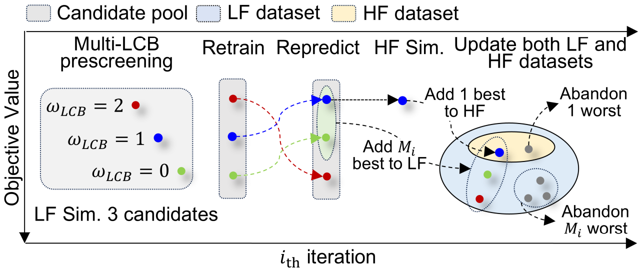

Fig. 2: The adaptive sample-replacement strategy.

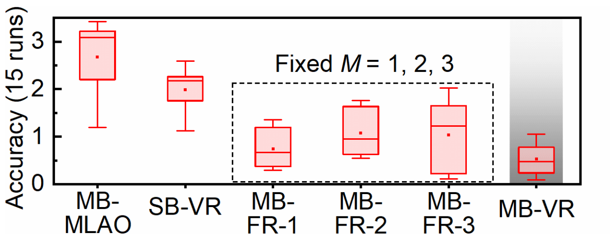

Fig. 3: Comparison of convergence accuracy results over 15 runs for D = 10.

added to the LF dataset, replacing the M least-contributing ones. Among these, the best-performing sample undergoes HF evaluation and replaces the least-contributing HF point. The replacement intensity M increases progressively with the iteration count t using:

$$M(t) = \min\left(M_{\max}, \left\lfloor 1 + \frac{M_{\max} t}{T} \right\rfloor\right) \tag{1}$$

where $M_{\max}$ is the number of LCB constants, T is the maximum iterations, and $\lfloor\cdot\rfloor$ denotes the floor function. This strategy keeps the datasets compact while capturing valuable information. The gradual increase of M will promote a logistic-like clustering pattern, enabling an initial extensive exploration and progressively focusing on the optimal region.

3 Numerical Validations and Conclusion

To evaluate the proposed BO method, we first test it on a multimodal multi-fidelity Ackley function. The method, incorporating both multi-LCB prescreening and varied replacement intensity (denoted as MB-VR), is compared with: (1) MB-MLAO [2], a multi-fidelity BO using only multi-LCB prescreening (ω = [0, 1, 2]); (2) SB-VR, the proposed method with single-LCB prescreening (ω = 2); and (3) MB-FR, the proposed method with fixed replacement intensities (M = 1, 2, 3). The experiments are conducted with a variable dimension of D = 10, a maximum of T = 200 iterations, and initial sample sizes of N_L = 100 (LF) and N_H = 20 (HF) within a boundary of [−3, 3]. Each test is repeated 15 times to ensure a statistical reliability. As shown in Fig. 3, the proposed MB-VR method demonstrates clear advantages in convergence accuracy, stability, and effectiveness of its variable replacement intensity strategy.

The proposed method is also applied to optimize a practical RFEH surface absorber [3] (Fig. 4), a dual-band 3×3 periodic array. The decision variable vector $\boldsymbol{x}$ = [a, b, h, s, g, w, x_1, x_2, y_1, y_2, R_L] is optimized to maximize the worst energy harvesting efficiency at 1.85 GHz (f_1) and 2.45 GHz (f_2), with a target efficiency of 50%. A multi-objective optimization problem (D = 11) is formulated as:

$$x^* = \operatorname*{argmin}_x \left\{ \max_{f_i} \{100 - \eta_i(x)\} \right\},\ i = 1, 2 \tag{2}$$

where η_i denotes the load absorption efficiency at frequency f_i. Fig. 5(a) compares the convergence curves of MB-MLAO, SB-VR, and the proposed method over 100 iterations, while Fig. 5(b) illustrates the frequency response of load absorption efficiency before and after optimizations by the proposed method. These results highlight the proposed BO method's superiority and effectiveness in advancing RFEH absorber designs.

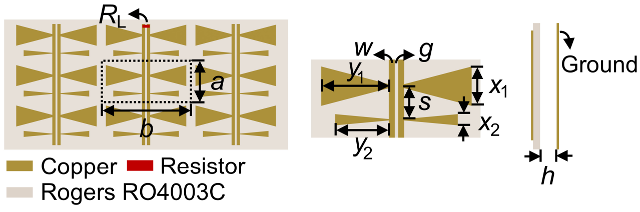

Fig. 4: Schematic diagram of the dual-band and scalable RFEH surface absorber.

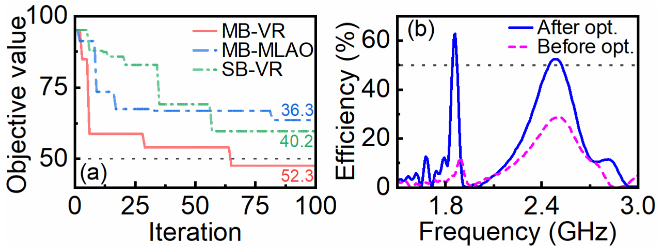

Fig. 5: (a) Convergence curves of three methods and (b) absorption efficiency before and after optimization using the proposed method (MB-VR).

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