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POWER SYSTEMS AND POWER ELECTRONICS

Bayesian optimization for solving high-frequency passive component design problems

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Abstract. In this paper, the performance of the Bayesian optimization (BO) technique applied to various problems of microwave engineering is studied. Bayesian optimization is a novel, non-deterministic, global optimization scheme that uses machine learning to solve complex optimization problems. However, each new optimization scheme needs to be evaluated to find its best application niche, as there is no universal technique that suits all problems. Here, BO was applied to different types of microwave and antenna engineering problems, including matching circuit design, multiband antenna and antenna array design, or microwave filter design. Since each of the presented problems has a different nature and characteristics such as different scales (i.e. number of design variables), we try to address the question about the generality of BO and identify the problem areas for which the technique is or is not recommended.

Key words: Bayesian optimization; high-frequency design; machine learning.

1. INTRODUCTION

When dealing with electromagnetic (EM) design of various RF & microwave components, designers need to find an optimal set of parameters describing the physical dimensions and material properties of the developed structure that realize the desired electrical specification. For this purpose, one often uses computer-aided design (CAD) software equipped with various optimization tools. Employing these optimization techniques allows for a faster, more efficient and semi-automated design process, as well as opens up the possibility of dealing with more complicated and highly integrated solutions. In EM design by optimization, the goal is most often to minimize the difference between the simulated and the desired function values, usually evaluated from the scattering parameters, radiation pattern or antenna gain. The set of optimal parameters is obtained by performing a series of EM simulations, which are most often carried out using the numerical methods, such as the method of moments (MoM) [1] or the finite-element method (FEM) [2, 3]. However, these methods are often expensive in terms of memory and computation time. In practical applications, the real challenge is related to the structural complexity of the devices, which are usually parameterized by tens of design variables. Therefore, both the time-consuming EM simulations and a large number of design variables become obstacles to finding an optimal solution.

Another difficulty regarding the use of the optimization schemes in high-frequency component design concerns the choice of the objective function, i.e. the qualitative expression for the fitness of the design. The outcome of the optimization task depends greatly on the definition of such a function. The designers would prefer their objective function to be easy to evaluate, with one global optimum and derivative information easily obtainable for the gradient-based algorithms [4]. In fact, in most cases the goal function is far more challenging to evaluate, has many local optima, and very often it is not feasible to provide the accurate derivative information to lead the optimizer. Therefore, the most commonly used gradient-based methods may become insufficient, thus a need for an alternative approach arises. If the local methods fail to optimize the problem, the design parameter space can be searched by utilizing one of the global optimization schemes [5–7].

One important category of global optimization techniques are evolutionary algorithms, among which are swarm-based methods, such as particle swarm optimization (PSO). PSO was introduced as a global optimization scheme in 1995 [8], and is based on the idea of natural behaviour of swarms or flocks of animals. The algorithm works with a population, i.e. a group of candidate solutions called particles, which is moved around the parameter space in every iteration in search of the global optimum. The particles are placed randomly in the search space and their fitness, i.e. the corresponding value of the cost function, is evaluated. Afterwards, each particle is given a value called velocity, which directs its movement to a new position that should provide a better fitness than the current location. The positions and velocities are updated iteratively based on the best location visited by each particle individually (personal best), as well as the information about the best location found by the entire population (global best). The new velocities are computed based on a set of control parameters, predefined for the whole optimization process, i.e. the acceleration constants, C_1 and C_2, controlling the contribution of the personal and global best, re-

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spectively, along with the inertia weight, ω, controlling the influence of the previous velocity, sometimes defined as variable depending on the iteration count, spanning from ω_1 to ω_2. The final values of the velocities are constrained in the range defined by $V_{\min}$ and $V_{\max}$. The population size parameter defines the number of particles, thus the number of function queries that will be performed in every iteration [9]. PSO has been chosen in this work because it is widely used for EM design optimization tasks, especially for antenna design problems [10–12]. This choice has proven to be a very effective optimization tool in various fields of engineering [13–15].

Another choice for this performance assessment is the random search method. It is one of the most straightforward ways to explore the unknown function parameter space. The idea of random search is based on sampling new candidate solutions from the function domain, within the known constraints, until the termination criterion is met. Such an approach is very simple, but can be successful given a sufficiently large number of function calls. Due to its simplicity and purely stochastic nature, it is a suitable way to test stochastic algorithms by comparison with the random search technique.

Other classes of global search schemes are the techniques based on surrogate models [16]. One way of building such an approximation model is Gaussian process (GP) regression, or kriging [17], which is the basis of Bayesian optimization (BO). BO has drawn attention in many fields of engineering, including the microwave & RF sector [18–22]. It is a machine learning approach aimed at optimizing black-box, expensive to evaluate functions. It is based on building a surrogate model of the function and taking informed decisions about the location of new function evaluations. The algorithm is greedy, i.e. the next evaluation point indicates the best possible improvement towards the optimum. The accuracy of the model increases when more points with known function value are gathered. BO has been widely used in the AI field for neural networks training and can be a very useful approach in other fields of engineering, particularly where the available budget of function queries is limited and there is little information about the cost function. One of the major drawbacks mentioned by researchers is the poor scalability of BO for problems with a high number of variables. This issue is addressed by several BO implementations and modifications [23].

This paper provides a practical review of BO performance in application to several different design problems, with comparison to other global optimization methods, i.e. PSO and random search. In order not to be limited to a specific realization of BO, three different algorithmic packages implementing the BO method have been examined: a standard Bayesian optimization procedure implemented in Bayeso [24], and two other packages modified for better scalability to high-dimensional problems: Dragonfly [23] and DPT-BO [19]. These two modified packages are expected to address the more complex EM design tasks with a large number of variables. Moreover, the DPT-BO algorithm is designed specifically for high-frequency electronic design, therefore it is anticipated to be a preferable choice for such problems. The test examples chosen for this study are all real-life design problems driven from various fields of the RF and microwave sector, namely, 1) minimizing losses in a substrate integrated waveguide (SIW) with air cavity, 2) matching a multifrequency antenna design, 3) forming the radiation pattern of a linear antenna array, and 4) a waveguide filter design with metal inductive strips. A detailed description along with a motivation for choosing these design tasks is provided in Section 4.

The rest of the paper is structured as follows. Section 2 describes the problem definition and goal function formulation for high-frequency electronic design by optimization. Section 3 provides a description of Bayesian optimization and GP regression. Section 4 demonstrates the performance of BO and other optimization methods on four design examples, which is further discussed in Section 5. The results are summarized in the conclusion in Section 6.

2. EM DESIGN BY OPTIMIZATION

Let us consider an optimization problem of minimizing an unknown function $f(x)$, which takes a vector of N parameters x as an input and returns a single value as an output (1)

$$\begin{aligned} x_{\min} &= \arg\min_{x \in X} f(x) \\ f &: X \to \mathbb{R}, \quad \text{where} \quad X \in \mathbb{R}^N. \end{aligned} \tag{1}$$

In EM design, the input vector represents the control parameters of the component being designed, which are most often the physical dimensions of the evaluated structure, such as the signal line widths, cavity lengths or others. The cost function is usually calculated as a difference between the desired and obtained value of the selected EM quality, e.g. the mean square error of the chosen output parameter $F_{(i)}$ for $i = 1, 2, \ldots, n$ frequency points under consideration (2). The comparison can be expressed as a difference or a quotient between the specified and acquired values

$$f(x) = \sqrt{\frac{1}{n} \sum_{i=1}^{n} \left| \frac{F_{spec.}}{F_{(i)}} \right|^2}. \tag{2}$$

The objective function in EM design tasks can also be expressed in other ways, e.g. in microwave filter design, defined using the location of zeros and poles of the filter transfer and reflection functions [25], or in antenna array design, by imposing the desired values in the specific angles of the radiation pattern, such as the side-lobe level or null locations [26].

3. BAYESIAN OPTIMIZATION

BO is a global optimization scheme that involves making decisions based on the gathered information, represented by a GP model. This approach originates from Bayes' theorem

$$P(y|\mathbf{D}, \theta) = \frac{P(\mathbf{D}|y, \theta) P(y|\theta)}{P(\mathbf{D}|\theta)}, \tag{3}$$

where y is the cost function value, $\mathbf{D}$ is the set of known pairs of parameters x_i and function values y_i, and θ are the hyperparameters defining the GP model. $P(y|\theta)$ and $P(y|\mathbf{D},\theta)$ are the probability distributions of the prior and the posterior measure over the objective, respectively, and $P(\mathbf{D}|y,\theta)$ is the likelihood. All of the above are conditioned on the parameters θ of the probabilistic model, which need to be chosen each time the model is updated to fit the given data.

3.1. Surrogate model: a Gaussian process

In Bayesian optimization, the prior measure over the objective function $f(x)$ is represented by a GP. It is a non-parametric model, which is defined by a mean function $\mu(x)$ and a covariance (or kernel) function $k(x,x')$. The popular choice for a kernel function are the squared exponential (SE) or Matérn-type functions [17]. The accuracy of the GP model depends greatly on the choice of these functions.

$$f(x) \sim GP(\mu(x), k(x,x')). \tag{4}$$

The GP model (4) represents the possible values that $f(x)$ may take in the function parameter space. The model also includes the uncertainty, which is narrow in close proximity to the known, evaluated points, and wider where there is no information about the values of $f(x)$. To better represent the goal function, the model is updated iteratively by performing a separate optimization of the hyperparameters θ during the optimization process.

3.2. Acquisition function

The BO process uses the surrogate model to decide where to take the next evaluation according to the selected acquisition function $\alpha(x)$. Such a function represents the probability of finding the optimum based on the actual GP model. The acquisition function may take various forms, among which the most commonly used formulas are expected improvement (EI) [27], probability of improvement (PI) [28], or upper confidence bound (UCB) [29]. Function $\alpha(x)$ is built in every iteration, after the GP model is updated. Afterwards, the BO procedure runs an optimization of $\alpha(x)$ to find the next point x_i to be evaluated in the i-th iteration, which indicates the most probable location of the goal function optimum. The maximum of the acquisition function is typically found with one of the gradient-based algorithms, such as the quasi-Newton method.

3.3. Bayesian optimization algorithm

The basic steps of Bayesian optimization procedure are shown in Algorithm 1.

Algorithm 1: Bayesian optimization procedure

```
initialization (random or previous knowledge);
while function count < function query limit do
    train the GP model (hyperparam. optimization);
    build α(x);
    optimize over α(x) to find the next point x_i;
    evaluate f(x_i);
    update the base of known x and f(x);
    function count = function count + 1;
```

The iterative procedure of BO involves running two separate optimization tasks at every iteration: optimizing the hyperparameters of the GP model and optimizing the acquisition function. This may lead to visibly longer computation times of the main optimization process in comparison to other global optimization methods, but can be neglected if a single function evaluation takes considerably more time and the available budget of function queries is relatively small. Such a scenario is also considered in this performance study (see Section 4.3).

4. TESTING BAYESIAN OPTIMIZATION FOR EM DESIGN

In order to examine the performance of BO for RF and microwave design purposes, the method has been applied to four different optimization problems from microwave engineering:

- minimizing losses in an SIW section with air cavity [19],
- multiband antenna matching [30],
- linear antenna array design [26],
- waveguide filter design [31].

An overview of these examples is presented in Table 1. These examples have been chosen to assess the aptness of the BO approach in a variety of RF design tasks for the following reasons: The SIW section can be treated as a good test case, as it has been introduced and analyzed successfully using a BO process in [19]. The antenna matching example represents a more challenging problem to evaluate with FEM, and thus it takes longer to perform a single EM simulation. In contrast, the third example is a linear antenna array, where a single function calculation takes a fraction of a second, but the number of function parameters is large. This case can be considered a stress test for the BO algorithms, which will show the contribution of the BO-related calculations. The last of the four examples, the waveguide filter, has a relatively small number of variables and a moderate duration of computations. It is therefore a suitable test case for every optimization method.

Table 1
A summarized description of the EM design problems chosen for optimization

Design problem	Number of parameters	Time of a single function query	Computation method
SIW section	12	30–45 seconds	FEM
Antenna matching	8	3–5 minutes	FEM
Antenna array	32	< 1 second	analytical
Waveguide filter	6	5 seconds	mode-matching

Each optimization task has been carried out with several global optimization techniques, including three BO packages: Bayeso [24], Dragonfly [23], and DPT-BO [19]. For comparison, the same tests have been performed using PSO and random search. All the computations were performed on an Intel i5-7400 workstation with 16 GB RAM. Because of the stochastic nature of the methods, at least five independent runs have been performed for each of them to generate the statistical report. This number of runs is a trade-off between the total computing time and the statistical accuracy of the results. It has to be noted that, as the DPT-BO package performs local gradient optimization for finding the GP model parameters, which is not stochastic, it does not need to be rerun for repeatability. In all examples, BO and PSO were run with the following settings:

- Bayeso: covariance function: Matérn 5/2, acquisition function: PI,
- Dragonfly: covariance function: Matérn 5/2, acquisition function: default (choosing from EI, UCB, TT-EI, ADD-GP-UCB) [23], updating the GP model every three iterations,
- DPT-BO: covariance function: Matérn 5/2 with automatic relevance determination (ARD) [32], acquisition function (PI, UCB, EI) chosen sequentially,
- PSO: $\omega_1 = 0.9$, $\omega_2 = 0.2$, $C_1 = 2$, $C_2 = 2$, $V_{\min} = -0.5$, $V_{\max} = 0.5$, according to [9].

Several sets of different settings were tested on the examples, and the configurations listed above provided better performance than others. Some of the selected settings were also presented as the default or recommended choice in these packages.

4.1. Example I: Substrate integrated waveguide

The first EM design-driven problem we investigate is the minimization of losses in an SIW section with an air cavity over the D-band (110–170 GHz). The structure and its geometric parameters are described in [19]. This example is suitable for this assessment, as it was used to demonstrate the capabilities of DPT-BO, with satisfactory results.

4.1.1. Definition of the optimization problem

In this case, the goal function (5) is based on the scattering parameters of the device and defined as the S21 and S11 values compared to the imposed level, set as $S_{21,\min} = -1.5$ dB and $S_{11,\max} = -13$ dB in the frequency range 110–170 GHz. The error is calculated as the ratio between the desired and obtained S-parameters for each frequency point in the selected band, covering a total of $n = 301$ frequency points. The RMS value of the error is computed as the output. The S-parameter response of the structure is calculated using a fullwave FEM simulator, InventSim [33]. The objective function has twelve parameters that define the physical dimensions of the SIW structure. The via holes in this project have been approximated by electric walls.

In order to improve the performance of the optimizers, the goal function used in [19] has been modified to the form presented in equation (5). Instead of just minimizing the value of S21, the goal was imposed on both S21 and S11, and the desired value in the selected frequency band is introduced

$$f(x) = \sqrt{\frac{1}{n}\sum_{i=1}^{n}\left(\left|\frac{S_{11,max}}{S_{11(i)}}\right|^2 + \left|\frac{S_{21(i)}}{S_{21,min}}\right|^2\right)}. \tag{5}$$

4.1.2. Results

The results are summarised in Fig. 1 as the value of the objective function compared to the number of function queries, and the best S-parameters found for each method are plotted in Fig. 2. A comparison of the runtimes is presented in Table 2.

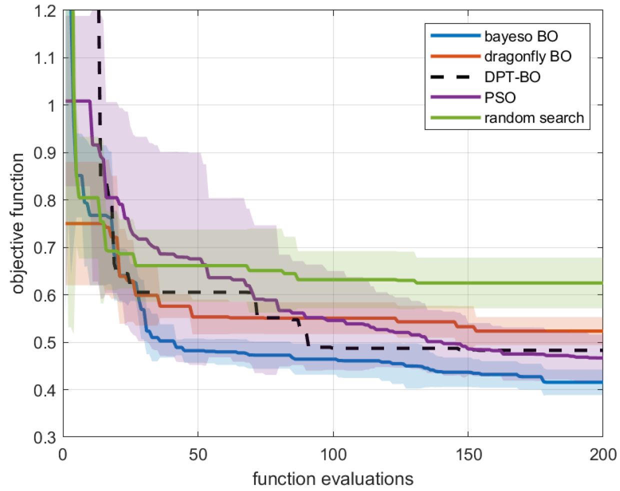

Fig. 1. Performance of the algorithms in minimizing loss in SIW. For the stochastic methods, the solid line is the mean and the shaded area represents the standard deviation from the mean

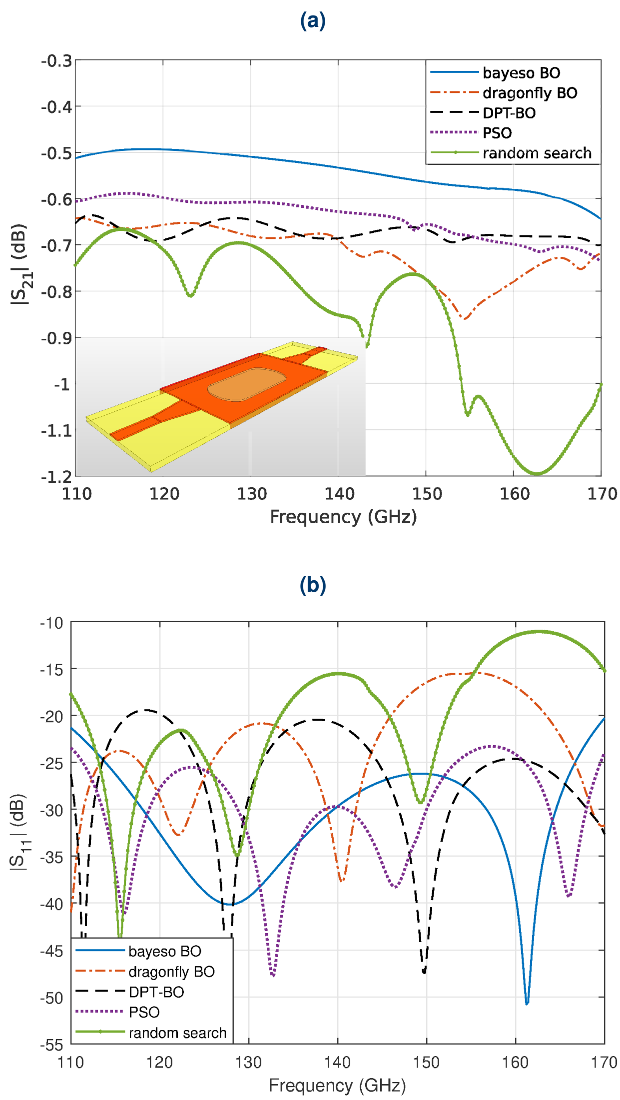

Fig. 2. SIW S-parameters: (a) |S21| comparison for different algorithms; (b) |S11| comparison for different algorithms

Table 2
Comparison of timing for SIW section optimization

Method	Elapsed time
Bayeso (BO)	4 h
Dragonfly (BO)	6 h 22 min
DPT-BO (BO)	3 h 10 min
PSO	2 h 36 min
Random search	2 h 34 min

The optimal design parameters for each method are summarized in Table 3. The tests have shown that BO provides sufficiently accurate results, but that PSO performs comparably or even better. The best results, with S21 above –0.6 dB and S11 below –25 dB from 115 to 165 GHz, were achieved using Bayeso. Moreover, all three BO methods showed the fastest convergence in the first fifty function queries. The overhead of Bayesian optimization can however be observed in the runtime. Here, the BO procedures take 20% (DPT-BO), 50% (Bayeso), or even 150% more time (Dragonfly) than PSO and random search. This additional time relates to the necessity of fitting the GP model and optimizing the acquisition function in every iteration. The duration of a single function query was approximately 30–45 seconds, so another 15–90 seconds of BO-related operations are extremely noticeable. According to the results of [19], the methods other than BO – namely, PSO and ADD-MES-G – could not find a relevant solution and became stuck in local optima. However, our research shows that slightly redefining the objective function and imposing separate conditions for S21 and S11 has made this design problem solvable for several global optimization schemes, and not only for BO.

4.2. Example II: Antenna matching

The next test deals with a design problem which takes considerably more time to be examined, namely a multifrequency microstrip antenna [30]. This design was chosen due to a possibly non-trivial task of optimizing the antenna for four different frequencies simultaneously. The 3D model of the structure, shown in Fig. 3, was once again prepared and analyzed with 3D FEM simulator InventSim.

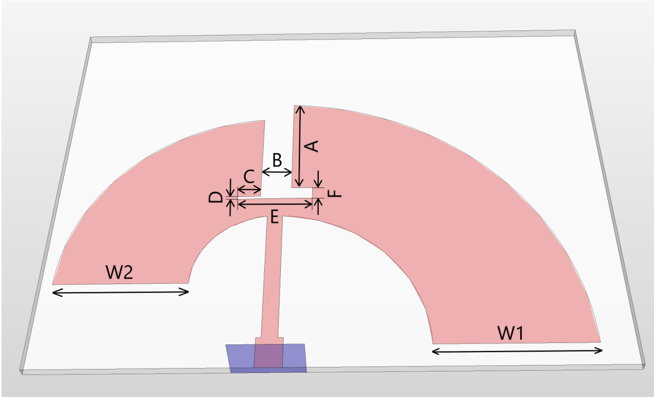

Fig. 3. Antenna 3D model in the InventSim FEM simulator

4.2.1. Definition of the optimization problem

The optimization task is to minimize the S11 parameter at all four desired frequencies of 0.9, 1.4, 1.8, and 2.4 GHz. The goal function is defined as the RMS error, expressed as the ratio of the desired and obtained S11 values, as in (6). The desired S11 level for each of the operating frequencies is set to –15 dB. The objective function takes eight parameters as an input: A–F defining the inverted T-shaped slot, and W1 and W2 determining the size of the one-quarter rings [30]

$$f(x) = \sqrt{\frac{1}{4}\sum_{i=1}^{4}\left|\frac{S_{11,goal}}{S_{11(i)}}\right|^2}. \tag{6}$$

4.2.2. Results

The antenna design was optimized by three BO packages, PSO, and random search. The results for all these methods are compared in Fig. 4. The mean and standard deviation of five independent runs is shown for all methods except DPT-BO. The best S-parameter results for each of the algorithms used is shown in Fig. 5. The best performance was observed for two of the BO packages, Bayeso and DPT-BO, which quickly converged towards the minimum in the first stage. PSO gave comparably good results after 200 function queries. However, the Dragonfly BO package and random search found less satisfying S11 characteristics, with the last resonance shifted above 2.4 GHz. The differences in computation times between BO and other methods are practically negligible, except for the Dragonfly al-

Table 3
Optimal design parameters found by each method for the SIW section example

Method	w_{SIW}	w_1	l_1	θ_w	l_2	t_c	h_1	h_2	r_1	r_e	Δ_w	h_e
DPT-BO (BO)	1.101	0.3	0.201	39.01	0.804	0.01	0.03	0.01	0.979	9.883	0.3	0.323
Dragonfly (BO)	1.188	0.288	0.225	40.13	0.85	0.011	0.029	0.015	0.233	9.375	0.15	0.934
Bayeso (BO)	1.1	0.3	0.343	47.93	0.408	0.012	0.013	0.01	0.211	8.963	0.453	0.1
Random search	1.286	0.297	0.408	44.54	0.953	0.012	0.021	0.018	0.961	2.014	0.546	0.186
PSO	1.15	0.3	0.215	30	1	0.01	0.013	0.014	0.173	1.5	0.139	0.184

The dimensions of w_{SIW}, w_1, l_1, l_2, t_c, h_1, h_2, r_1 and Δ_w are in millimeters, θ_w in degrees, and r_e and h_e are ratios, all defined in [19].

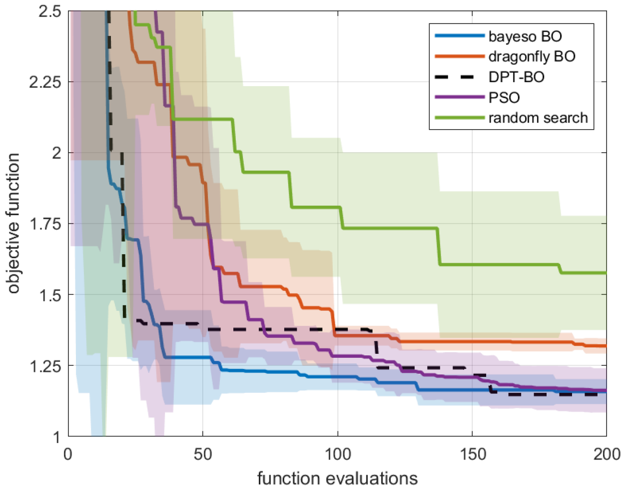

Fig. 4. Performance comparison for the multifrequency antenna matching design problem

gorithm, as shown in Table 4. In this design problem, a single EM simulation took approximately 3–5 minutes to perform, depending on the FEM mesh size. The extra BO-related computations did therefore not visibly affect the overall optimization time. Even the slowest method, Dragonfly, took 13% longer to compute than PSO or random search – a small downside compared to the 150% time increase in the previous example.

Table 4
Timing comparison for the antenna matching example

Method	Elapsed time
Bayeso (BO)	13 h 32 min
Dragonfly (BO)	14 h 48 min
DPT-BO (BO)	13 h 22 min
PSO	13 h 5 min
Random search	13 h 4 min

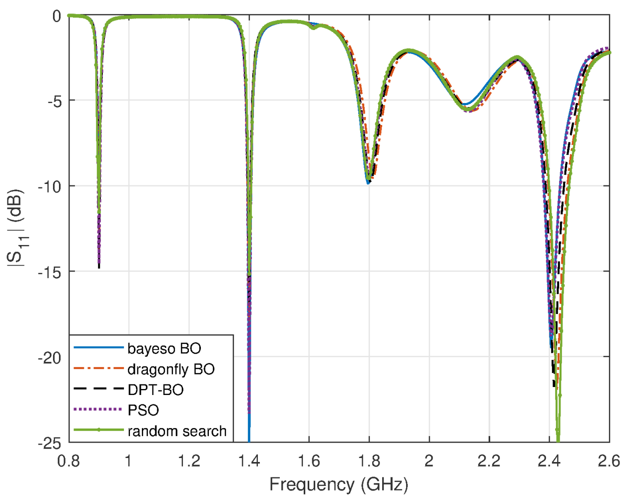

Fig. 5. Antenna S11 characteristics comparison

4.3. Example III: Linear antenna array

Another type of antenna design problem where the optimization is required is antenna arrays. For the purposes of this performance assessment, an array factor of linear antenna array with variable amplitudes and phases was analyzed. The following example was computed analytically, the expressions for calculating the array factor (AF) were derived from [26]. The spacing between neighbouring elements is assumed constant and equals $d = \lambda/2$. Please note that such a problem usually leads to optimization of a function with many parameters, but the time of a single function evaluation is short comparing to the EM analysis time shown in other examples. Therefore, this design example is an important part of the BO performance study as it emphasises the total duration of a single iteration, especially the internal computations that are the bottleneck of BO algorithms. Another serious challenge in this case is the high dimension of the problem, a disadvantage which often disqualifies BO. Here, two BO implementations modified for better scalability, namely Dragonfly and DPT-BO, have been proposed to tackle this issue.

4.3.1. Definition of the optimization problem

The optimization goal was to form the radiation pattern to suppress the side-lobe level (SLL) at the specified angles. An example representing a sixteen-element array was prepared as in [26], pp. 168–170: the radiation pattern was specified as in Fig. 6. The main lobe was set at the desired values, spanning from 0 to –13 dB, at an angle θ spaced in 5° increments between 90° and 140°. The restriction on SLL was –20 dB for $\theta \in [0°, 65°]$ and –35 dB for $\theta \in [65°, 88°]$. Another goal component was the nulls in the radiation pattern, defined by an AF level of –60 dB at $\theta_{\text{null}} = \{20°, 35°, 45°, 55°, 65°, 72°, 78°, 84°, 88°, 143°, 155°\}$. The cost function inputs are the amplitudes and phases of each radiating element, making a total of 32 parameters. Once again

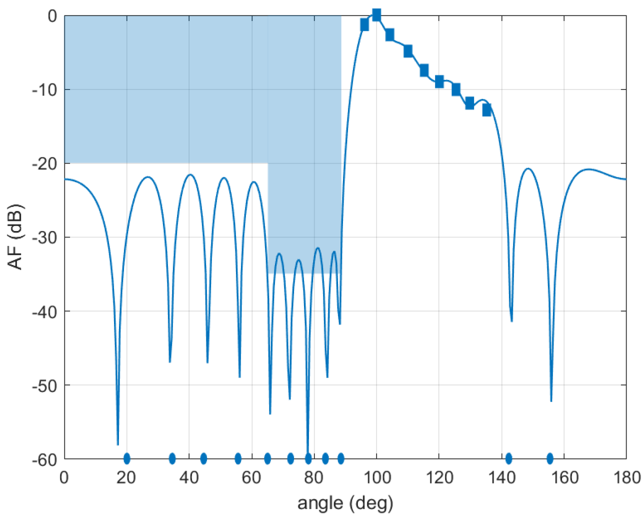

Fig. 6. Specified array factor for a sixteen-element array [26]. The shaded areas are masks imposed on the SLLs, the dots indicate the null locations, and the rectangles show the desired shape of the main beam

the cost function output is computed as the RMS value of the error, considered as a deviation from the desired characteristics, listed above.

4.3.2. Results

The results are summarized in Table 5, and the patterns found by each method are plotted in Fig. 7. The time limit chosen for solving this optimization task was three hours. The comparison clearly shows that BO fails to find the global optimum and is not suitable for this category of problem. In antenna array design, the goal functions are highly multidimensional, and even the BO modifications specifically recommended for problems with a large number of variables, here DPT-BO and Dragonfly, show very poor performance and apparently fail to build a good surrogate model in the high-dimensional parameter space. Another drawback of the BO approach is the time taken for updating the GP model and optimizing the acquisition function, which are performed for every iteration. Here, the cost function takes seconds to evaluate and hence can be called multiple times, while the BO-related processes take minutes. This is why in such cases, the most efficient optimization procedures are evolutionary algorithms, where hundreds of function queries can be processed in parallel. In Bayesian optimization, however, running more than a thousand function evaluations is impractical, as it leads to extremely long computation times. Ten independent solutions found with PSO are plotted in Fig. 8. These results were obtained with 10 000 function queries and a swarm population of 40. For this configuration, the radiation pattern meets most of the specified requirements, except for the –35 dB SLL level for angles $\theta \in [65^\circ, 88^\circ]$; however, a –30 dB level was achieved. Conversely, the results provided by PSO with only 2000 queries did not meet the expectations: the SLLs were above –20 dB and the null locations did not agree. This example was also optimized with the covariance matrix adaptation evolution strategy (CMA-ES) method [34], which is another representative of evolutionary algorithms, and similarly to PSO, works on a population of samples and performs multiple function queries in every iteration. Here, CMA-ES algorithm was run for 200 iterations, with a population of 140, which results in 28 000 function evaluations. The solution found by CMA-ES meets all requirements and shows that population-based methods are particularly effective for such category of optimization problems.

Table 5
Comparison of methods for antenna array optimization

Method	Function queries	Computation time	Optimization result
DPT-BO (BO)	244	3 hours	not optimized (goal value: 18.9)
Dragonfly (BO)	128	3 hours	not optimized (goal value: 18-20)
Bayeso (BO)	360	3 hours	not optimized (goal value: 15-20)
Random search	2000	6–10 seconds	not optimized (goal value: 15–18)
Random search	10 000	30–50 seconds	not optimized (goal value: 13–15)
PSO	2000	0.9–1.3 seconds	not optimized (goal value: 6.5–9)
PSO	10 000	4.0–4.5 seconds	**optimized** (goal value: 4.2–6)
CMA-ES	28 000	10–12 seconds	**optimized** (goal value: 4–6)

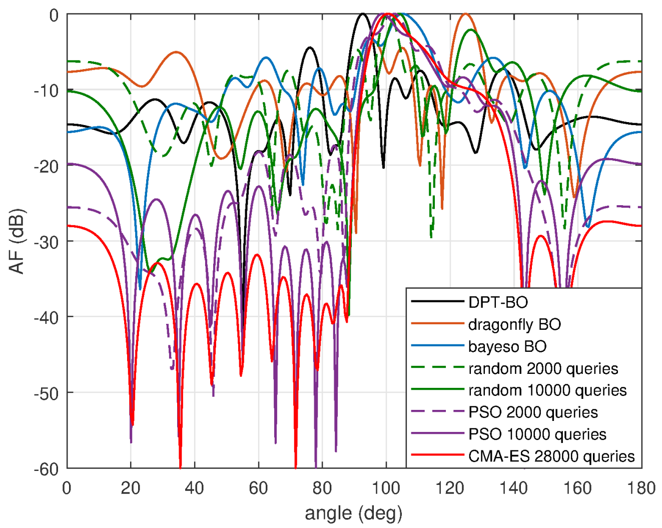

Fig. 7. Antenna array factor: the best solutions found by each method

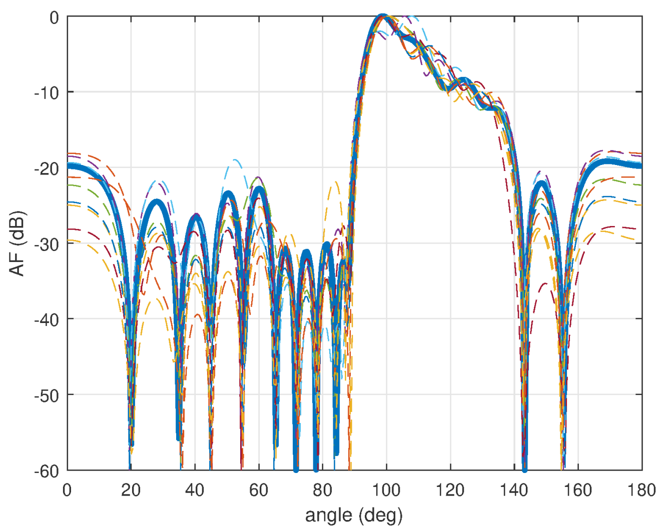

Fig. 8. Antenna array factor: ten independent solutions found by PSO after 10 000 function queries. The bold line indicates the best solution

4.4. Example IV: Waveguide filter

The final category of EM design problem investigated here is the microwave filter. Microwave filter design by optimization is one of the most demanding optimization problems in the field of computational electromagnetics, so there is an ongoing search for faster and more efficient ways to perform such tasks [35]. The structure considered here is a fifth-order waveguide filter with E-plane metal inserts inside, shown in Fig. 9. The waveguide filter was analyzed numerically using FEM and semianalytically with the mode-matching method [36]. The latter was selected for further study due to the short time needed for a single analysis.

The aim here was to choose the optimal values for the subsequent waveguide sections to design a filter implementing the Chebyshev band-pass filtering function [31]. In this case, the center frequency f_0 is 10 GHz, and the bandwidth is 800 MHz. The desired return loss (RL) is 25 dB, and the out-of-band rejection at $f_0 \pm 700$ MHz is 10 dB. The filter response is calculated for 201 frequency points, spanning from 9 to 11 GHz. The structure is symmetrical about the center and can be described by six control parameters: three lengths of the E-plane metal diaphragms, a_1, a_2, a_3; and three lengths of the waveguide sections, L_1, L_2, L_3 (resonant cavities).

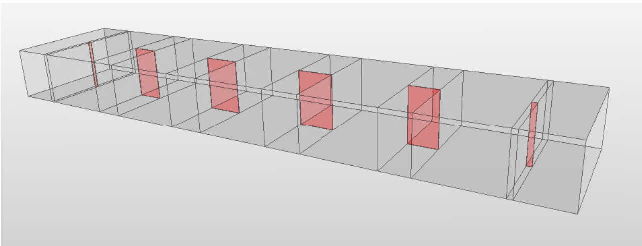

Fig. 9. Waveguide filter with metal inserts

4.4.1. Definition of the optimization problem

The goal was to achieve the desired filter response in the selected band. The objective function was defined for S11 in the passband and S21 in the stopband, in accordance with the formulas proposed in [37]. This type of goal function is commonly used in practical filter design. Here, the desired S11 level in the passband is –25 dB, and the S21 level in the stopband, i.e. 9.0–9.3 and 10.7–11.0 GHz, is –10 dB. The passband is evaluated in a total of $n = 81$ frequency points, i.e. 9.6–10.4 GHz, and the stopband corresponds to $m = 62$ frequency points of the calculated response. The function output is the root of the averaged sum of errors calculated for each frequency point, as shown in equation (7)

$$f(x) = \sqrt{\frac{1}{n}\sum_{i=1}^{n}\left|\frac{S_{11,spec.}}{S_{11(i)}}\right|^2 + \frac{1}{m}\sum_{j=1}^{m}\left|\frac{S_{21,spec.}}{S_{21(j)}}\right|^2}. \tag{7}$$

4.4.2. Results

The tests were run with the same group of BO packages, as well as PSO and random search. The results are summarized in Fig. 10. None of the global optimization methods managed to find a acceptable filter response, as can be observed in Fig. 11. In order to show that an acceptable result can be achieved, the following example has also been solved by generalized Chebyshev optimization tool available in InventSim electromagnetic field simulator. This optimal response is compared with the best response found using global optimizers in Fig. 12. The optimal design parameters are: $L_1 = 13.714$, $L_2 = 14.112$, $L_3 = 14.153$,

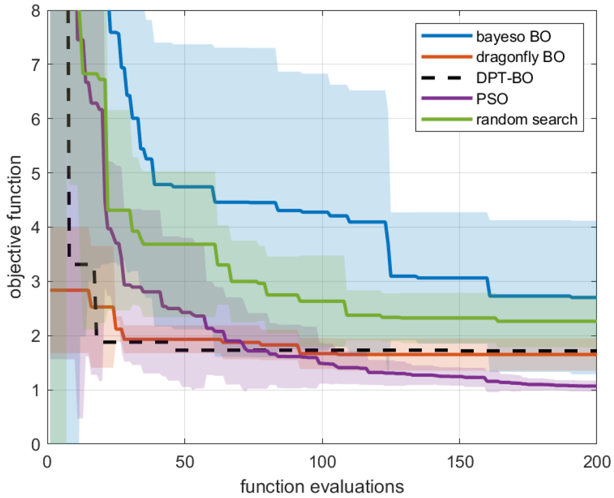

Fig. 10. Comparison of results for a fifth-order waveguide filter example

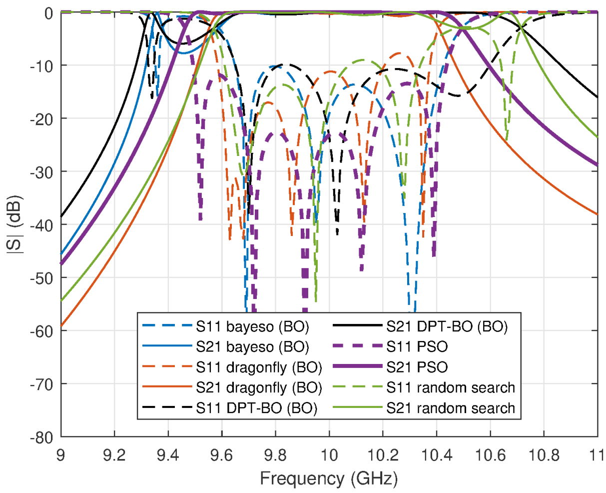

Fig. 11. The filter responses found by each method. The best results were found with PSO (bold purple lines)

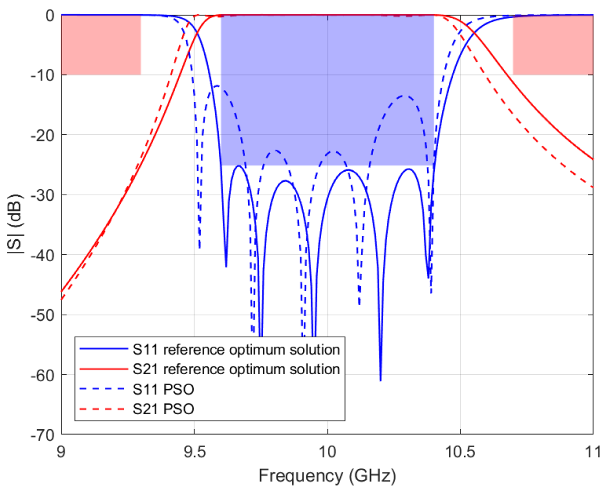

Fig. 12. Comparison of the best filter response found by global optimization (PSO) and the reference optimum solution. The shaded areas are the masks determined by the optimization goal

$a_1 = 0.5947$, $a_2 = 4.523$, $a_3 = 6.063$. All values are in millimeters. The aimed-for response is thus realizable in the structure, but the global algorithms failed to find the correct solution.

5. DISCUSSION

In this paper, three BO algorithms were tested on four high-frequency design problems of different nature. These methods performance is summarized in Table 6. All three BO packages have managed to optimize the SIW example, and also, with varying success, the multifrequency antenna matching. However, the other two test cases showed certain limitations that BO failed to overcome. The example of a sixteen-element antenna array represents a high-dimensional design case, which clearly demonstrates that the problem of dimensionality is still a serious BO limitation, even for dedicated modifications. The waveguide filter example shows that BO is not only subject to the number of function parameters, but more importantly, the nature of the cost function. Here, the microwave filter optimization problems often deal with objective functions of high variance, where the optimum is located in a narrow valley and there are many local optima [6]. Apparently, this function type is difficult to model, regardless of the small number of variables. The shape of the cost function can thus also stand in the way of a successful BO process.

Table 6
Summary of the performance of the BO algorithms and reference methods

Method \ Problem	SIW (12 dim.)	Antenna matching (8 dim.)	Antenna array (32 dim.)	Waveguide filter (6 dim.)
Bayeso (BO)	optimized	optimized	not optimized	not optimized
Dragonfly (BO)	optimized	poorly optimized	not optimized	not optimized
DPT-BO (BO)	optimized	optimized	not optimized	not optimized
PSO	optimized	optimized	optimized	not optimized
Random search	poorly optimized	poorly optimized	not optimized	not optimized

The dimensions of each problem search space are provided in parenthesis.

6. CONCLUSIONS

The performance of Bayesian optimization for various EM design problems has been assessed. BO was tested and compared with other global optimization techniques in four different optimization tasks taken from the RF and microwave sector. Our analysis has shown that BO is subject to numerous limitations, and therefore may not be the best choice for many EM design procedures. Optimization based on Bayesian inference is preferred for tasks with a small number of function parameters, where a single function evaluation is costly in terms of time and computational resources. It should also be noted that, based on our test examples, for a certain class of problems such as microwave filter optimization, BO performs poorly and may not be a suitable tool. However, the idea of applying machine learning methods to the RF and microwave sector continues to attract attention, and future modifications of BO and related techniques may overcome these obstacles.

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