Fast, Robust and Global Optimisation for Antenna Design using Meta Modelling

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***Abstract*—This paper introduces a data-driven meta-modelling framework designed to optimize challenging antenna designs, addressing the limitations of traditional gradient-based - and global search methods. The framework utilizes Bayesian Optimization (BO) and High-Order Gaussian Processes (HOGPs) to approximate black-box functions, substantially reducing the reliance on full simulations. Two case studies that 1) optimises a multi-section corrugated horn antenna and 2) balances gain and return loss in a dual-reflector system, demonstrate the framework's effectiveness in handling complex design challenges, offering a scalable and efficient tool for antenna engineers.**

***Index Terms*—antennas, electromagnetics, surrogate modeling.**

I. Introduction

Modern antenna design for space applications, such as telecommunications or Earth observation, requires high-precision fine-tuning of both geometric and material parameters to meet stringent performance specifications. This necessity becomes even more pronounced as the design process advances, making it mission-critical to achieve absolutely optimal performance. In many cases, the fine-tuning task can effectively be addressed using advanced simulation-based optimisation software. However, general-purpose optimization algorithms, including gradient-based methods [1] and meta-heuristics [2], [3], typically lack robustness and rely on a large number of electromagnetic (EM) simulations to identify the optimal design parameters. These methods are often challenged by the need of repeated simulations, complex design landscapes and the need to manually adjust parameters to reflect preferences and balancing multiple performance criteria.

To address the challenges of conventional optimization methods, this work proposes a data-driven meta-modelling framework for black-box, compute-intensive antenna design tasks. In this context, meta-modeling refers to machine learning-based approximations to full-scale EM simulators, built from carefully selected simulation data. The key benefit is that meta-models can in many cases effectively replace true EM simulations for practical purposes, offering significantly faster evaluations while retaining sufficient accuracy [4]. The proposed framework is aimed at tackling antenna design tasks where conventional methods may struggle, particularly those involving expensive black-box objective functions, unavailable or costly derivatives, complex optimization landscapes with multiple local optima, uncertain starting-guesses, and designs that require consideration of multiple frequencies and criteria.

To allow antenna engineers to address such design tasks more efficiently, the proposed framework uses Bayesian optimisation (BO), which is particularly well-suited for optimising expensive black-box functions using low volume data [5], [6]. Using BO, the framework offers a robust alternative to conventional optimization methods by eliminating the need for gradient information, making it well-suited for problems with expensive objective functions and uncertain initial guesses. Additionally, the meta modelling framework provides a more sample efficient approach than global search methods, like genetic algorithms or particle swarm optimization, offering faster convergence and reduced computational costs. To showcase the framework's potential, this paper considers two case studies. Case study I uses the framework to optimise a multi-section corrugated horn antenna to be used in a Compact Antenna Test Range (CATR) similar to HERTZ 2.0 [7], while Case study II considers a multi-criteria design problem, where the goal is to optimally balance the conflicting objectives of gain and return loss for a dual reflector system. Case study I aims to show the robustness of BO as a global optimiser, while Case study II serves as a conceptual example of an antenna design task, that would be both highly time-consuming and cumbersome using traditional methods.

The paper is structured as follows: Section II introduces the meta-modeling framework. Section III presents the CATR case study, while Section IV covers the dual reflector, multi-criteria design study. Section V draws overall conclusions.

II. Meta-Modelling Framework

The primary objective of the meta-modelling framework is to address large-scale, black-box optimization problems of the form:

$$\begin{array}{ll} \text{minimize} & h\left(\boldsymbol{r}\left(\boldsymbol{x}\right)\right) \\ \text{subject to} & \boldsymbol{l} \leq \boldsymbol{x} \leq \boldsymbol{u} \end{array} \tag{1}$$

where $\boldsymbol{x}$ are the variables and $\boldsymbol{l}, \boldsymbol{u}$ constitutes lower and upper bounds. h is the scalarisation of the vector function, often taken to be the *min-max*, such that $h\left(\boldsymbol{r}(\boldsymbol{x})\right) = \max_{i=1,\ldots,M}\left(r_i(\boldsymbol{x})\right)$, and the residuals $\boldsymbol{r}$ are defined as

$$r_i(\boldsymbol{x}) = w_i\left(g_i - f_i\left(\boldsymbol{x}\right)\right), \quad i = 1, \ldots, M. \tag{2}$$

Here, w_i and g_i constitutes the weight and goal-value of the i'th residual. Most importantly, f_i contains the performance of interest, e.g. the sidelobe-level, gain, etc. While many optimization problems (1) can be solved with conventional gradient-based or global search algorithms, challenges arise when dealing with expensive, black-box objective functions, as these rely on repeated simulations to compute the residuals. In such cases, first- and second-order derivatives may be unavailable or costly to approximate, and the optimization landscape might have multiple local optima. Moreover, if changes in objective function h, weights (w_i), or goals (g_i) are needed during the design process, the optimization must be restarted, wasting expensive computations of the residuals $r_i(\boldsymbol{x})$.

A. Meta-Modelling and Bayesian Optimization

To reduce the computational burden of solving compute-intensive antenna design tasks, meta-modelling seeks to replace expensive black-box functions $\mathbf{F} : \mathcal{X} \subset \mathbb{R}^i \to \mathbb{R}^o$ with a fast, cheap-to-evaluate approximation $\mathbf{G}(\boldsymbol{x}) \approx \mathbf{F}(\boldsymbol{x})$, enabling efficient exploration of the design space. Among various meta-modelling techniques, Gaussian Processes (GPs) [8] stand out for their ability to provide both predictions and uncertainty estimates, making them ideal for optimisation tasks. Concretely, Bayesian Optimization (BO) integrates GPs into an iterative framework that efficiently explores the design space by balancing exploration and exploitation. The key steps in BO include (See Fig. 1):

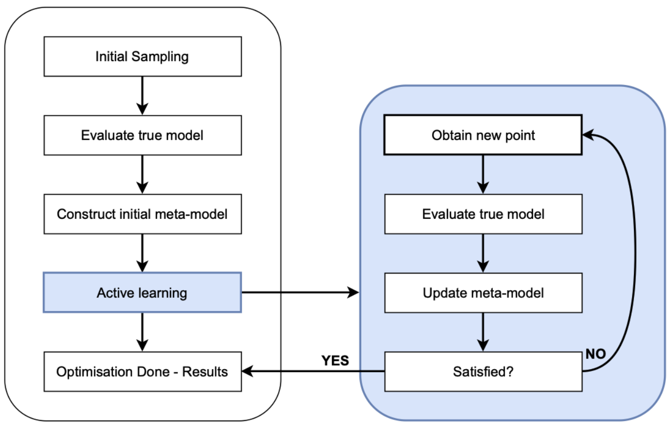

Fig. 1. Bayesian Optimisation workflow

1) **Initial Sampling:** An initial set of sample points is generated, often using low-discrepancy sampling methods, to cover the design space.
2) **Meta-Model Construction:** A meta-model is trained on the initial data, modeling both the objective function and the uncertainty in its predictions.
3) **Active Learning:** An acquisition function is used to select the next sample points, balancing exploration (sampling in high-uncertainty regions) and exploitation (focusing on promising areas).
4) **Iterative Refinement:** The selected design is evaluated using the true function, and the meta-model is updated with the new data. This process repeats until convergence or a stopping criterion is met.

B. Main Contributions

Although BO is a well-established concept [4], the primary contribution of this work is the specific adaptation of meta-modelling and BO for tackling challenging antenna design tasks with many residuals, achieved through two key components:

- **High-Order Gaussian Processes (HOGPs)** Unlike conventional single-output GPs, which model h or treat each output $r_i(\boldsymbol{x})$ independently, the work uses High-Order Gaussian Processes (HOGPs) [9] to model multiple outputs simultaneously, capturing complex correlations between them. This approach significantly enhances the efficiency and scalability of the meta-modelling framework, particularly when dealing with thousands of residuals, $r_i(\boldsymbol{x})$, as is often the case in antenna design tasks.
- **Log Expected Improvement Acquisition Function** Another key contribution of this work is the use of the Monte Carlo (MC)-based Log Expected Improvement (LogEI) acquisition function [10], [11]. LogEI addresses the challenges of vanishing gradients in high-dimensional spaces by transforming the Expected Improvement (EI) function into log-space, thereby stabilizing gradient computations and enhancing optimization performance in complex design landscapes.

Overall, the proposed framework combines meta-modelling with Bayesian Optimization (BO), leveraging HOGPs and the robust LogEI acquisition function to efficiently tackle large-scale, challenging antenna design problems. The novelty lies in the multi-output modelling capability of HOGPs and the numerically stable acquisition function, enabling BO to explore and exploit complex design spaces with minimal computational effort, making it a powerful tool for addressing compute-intensive antenna design tasks with complex design landscapes.

III. Case Study I - Bayesian Optimisation of a Multi-Section Corrugated Horn Antenna

This case study applies the meta-modelling framework to optimise a multi-section corrugated horn antenna to be used in a typical Compact Antenna Test Range (CATR) [7]. The goal of the optimisation is to shape the individual sections of the horn to produce a flat-top radiating pattern in the broadband range from 1.3-1.5 GHz. Coverage of multiple frequencies is desired to allow for a single, multi-purpose device. The use of a multi-section corrugated horn, as opposed to a simple parameterized profile, is motivated by [12], showing that multiple sections offer the designer sufficient degrees of freedom to produce the desired board band flat-top radiation pattern.

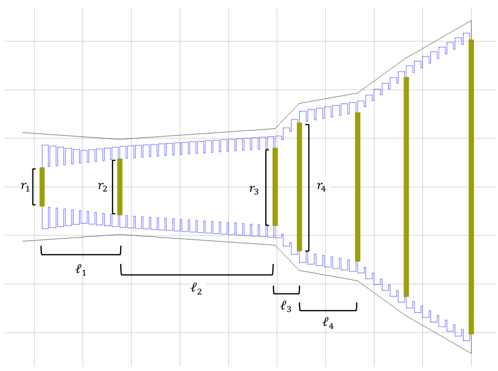

Fig. 2. Profile of the intentionally suboptimal initial horn design to demonstrate BO's robustness.

A. Initial Horn Design

The corrugated horn antenna consists of six circularly symmetric horn sections, defined using CHAMP3D [13]. The seven circular waveguide ports connecting these sections are characterized by radii r_i, and each section has a length ℓ_j (See Fig.2). Mode matching is applied to solve each section, while the radiating aperture is efficiently analyzed using Body-of-Revolution Method of Moments (BoR MoM) [14]. To demonstrate the robustness of BO in handling poor initial conditions, the case study focuses on an intentionally suboptimal design, as shown in Fig. 2. This suboptimal design was generated by perturbing the design variables from a previously optimised structure.

B. Optimisation goals

The optimisation goal is to achieve a rotationally symmetric flat-top radiation pattern around $\theta = 0$ degrees, across a broad range of operating frequencies. To this end, the RHC components are optimised at three selected frequencies, $f_1 = 1.3$ GHz, $f_2 = 1.4$ GHz, and $f_3 = 1.5$ GHz, to closely match the target template shown in Fig. 3. The far-field is sampled with a resolution of 1 degree for θ and 30 degrees for ϕ, resulting in 120 sampling points per frequency, yielding a total of 720 residuals across the three frequencies. The design variables subject to optimisation are r_1, r_2, r_3, r_4, ℓ_1, ℓ_2, ℓ_3, and ℓ_4, as shown in Fig. 2. Table I lists the corresponding initial values along with the lower - and upper bounds.

C. Results

The Bayesian Optimization (BO) algorithm is compared to the state-of-the-art global optimization method, Multi-level Coordinate Search (MCS) [15]. Both approaches are allocated a budget of 100 true function evaluations. BO successfully identifies the better design after 61 evaluations with a maximum deviation of 0.1531 dB from the goal template, whereas MCS required 91 evaluations to find a suboptimal design with a maximum deviation of 0.1782 dB. The resulting flat-top radiation patterns are shown in Fig. 4 and Fig. 5 for BO and MCS, respectively. It is clear that BO produces a pattern closer to the goal template across the selected frequencies. The final horn profile, optimised with BO, is shown in Fig. 6.

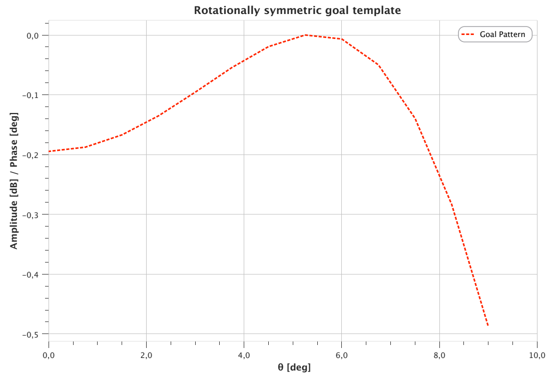

Fig. 3. The target goal template.

Variable name	Initial value	Lower bound	Upper bound
r_1	100	80	120
r_2	145	110	180
r_3	200	180	240
r_4	330	200	460
ℓ_1	400	280	520
ℓ_2	800	600	1000
ℓ_3	125	100	150
ℓ_4	300	210	390

TABLE I
THE INITIAL VALUE AND BOUNDS FOR THE 8 OPTIMISATION VARIABLES. ALL VALUES ARE IN MM.

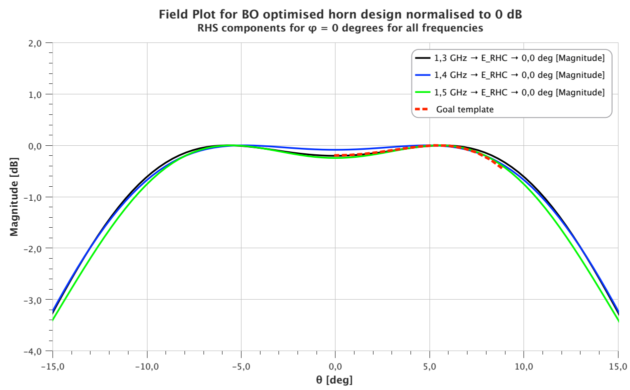

Fig. 4. RHC components of the BO optimised horn.

IV. Case Study II - Multi-objective optimisation

To showcase the potential of the meta-modelling framework to solve truly computationally expensive antenna design tasks, this case study addresses the common challenge in antenna design of balancing conflicting performance criteria. Specifically, the study focuses on optimizing a dual-reflector antenna system consisting of two rotationally symmetric reflectors, with a main reflector diameter of 1.5 m and a subreflector

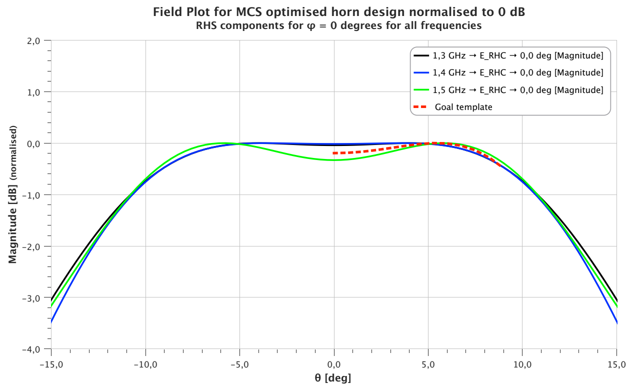

Fig. 5. RHC components of the MCS optimised horn.

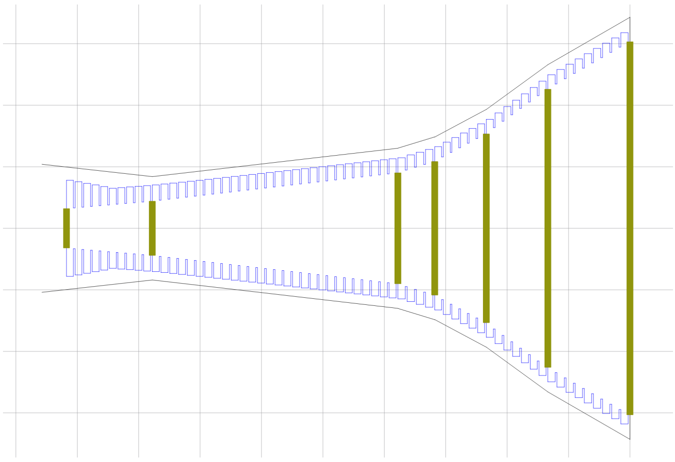

Fig. 6. BO optimised horn profile.

diameter of 0.225 m (See Fig. 7). The system operates at 8 GHz and is modeled in CHAMP3D [13] using mode matching for the horn interior and BoR MoM [14] for the horn exterior and the reflectors, ensuring fast analysis.

A. *Optimisation goal*

The optimization task involves shaping the geometry of the subreflector using eight design variables, where the primary goal is to optimally balance the conflicting objectives of gain and return loss. Traditionally, balancing these conflicting objectives requires single-objective optimization, where the engineer manually adjusts goal weights w_i to reflect the relative importance of each performance criterion. This process can be time-consuming and inefficient, as the engineer must perform multiple optimization runs to explore the various trade-offs reflected by w_i. Additionally, choosing appropriate weights is non-trivial, as the performance criteria often differ in scale and units, making it challenging to accurately reflect the engineer's preferences. As a result, this approach becomes computationally expensive, time-consuming and the manual approach limits the ability to dynamically explore multiple trade-offs during the optimization process. Ultimately, this may lead to unexplored design options.

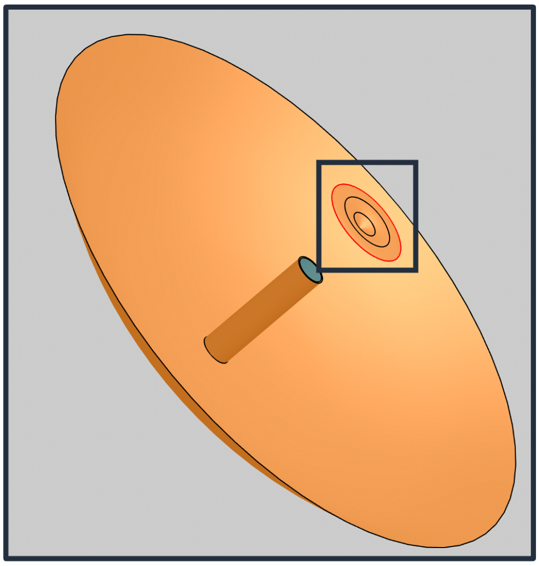

Fig. 7. Axially displaced ring focus dual-reflector system. The goal is to shape the geometry of the subreflector using 8 design variables.

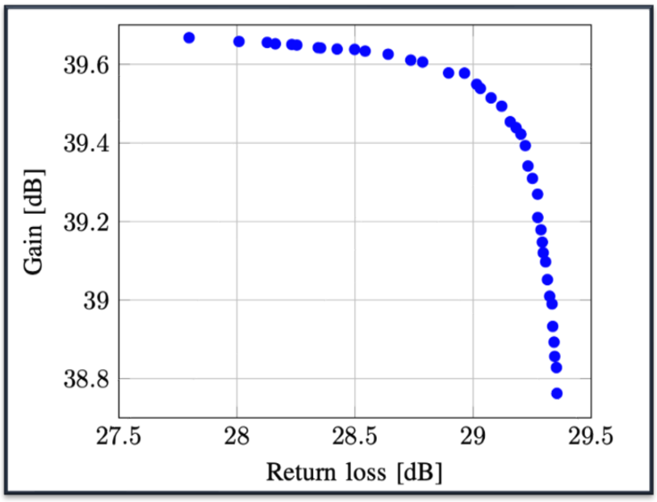

Fig. 8. The generated Pareto front of optimal trade-offs between gain and return loss. Using a traditional algorithm, each point on the frontier corresponds to a optimal design and would require a full optimisation to compute.

B. *Multi-criteria formulation using meta-models*

The meta-modelling prototype overcomes the limitations of traditional methods by combining meta-models with multi-objective optimization. In this case study, the NSGA-II multi-objective algorithm [16] is combined with a meta-model to simultaneously find all optimally balanced trade-offs, providing the engineer with the complete overview for different designs. To make the computation feasible in practice, the idea is to only use true function evaluations, whenever the meta-model is uncertain in its predictions, thereby significantly reducing computational complexity.

C. Results

The results, as shown in Fig. 8, demonstrate the wide range of potential trade-offs between gain and return loss, known as the Pareto front. In a conventional setup, generation of the frontier will often be practically intractable as each data point represents a full single-objective optimisation. In contrast, the combination of NSGA-II and meta-modelling allows the engineer to perform visual inspection of the frontier, providing a near complete picture of the possible trade-offs. For instance, improving the gain by approximately 0.8 dB can be achieved by accepting a reduction in return loss of around 1 dB. Of the 4000 evaluations required by NSGA-II, only 134 needed full simulations, while the remaining 3866 evaluations were handled by the GP meta-model. This approach reduced computational costs by 97%, making the exploration of complex design spaces both feasible and efficient.

V. Conclusion

In conclusion, the proposed meta-modelling prototype offers a robust and efficient alternative to traditional optimization methods, particularly for antenna design problems with expensive, black-box objective functions and poor starting guesses. By leveraging BO with HOGPs, it enables efficient exploration of complex, multi-residual designs, outperforming global methods. While BO excels in challenging scenarios, it is not to be considered a silver bullet. In fact, local optimization remains preferable when good starting points or derivative information are available, and global methods are more practical for inexpensive, well-constrained problems. As such, BO is meant to fill the critical gap for handling complex antenna design tasks where conventional methods fall short.

Overall, the case studies demonstrate the significant potential of the meta-modelling framework to expand the scope of antenna designs that can be explored within practical time frames. By allowing engineers to efficiently balance multiple performance criteria with minimal computational overhead, the framework offers a scalable solution for addressing complex optimization challenges in antenna design, where conventional algorithms are often found to struggle or become cumbersome.

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