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RESEARCH ARTICLE

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An Efficient Model for Complex Antenna Design and Development Using Self-Adaptive Machine Learning-based Optimization Algorithm

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Abstract

Surrogate Systems (SS) are extensively employed in antenna design to enhance optimization effectiveness.The targeting antennas frequently have limited design parameters and requirements, resulting in a brief SS training duration. Contemporary antennas are becoming progressively intricate, necessitating a more significant number of design parameters and requirements, rendering the training duration a new constraint, which sometimes exceeds the time required for Electromagnetic (EM) modeling.This study presents a novel training cost-reduction-basedSS for a complicated antenna-optimizingmodel. The principal advancements comprise: 1) a self-adaptive Gaussian procedure SS technique that markedly decreases training duration while preserving antenna efficiency accuracy in forecasting, and 2) a novel mixed SS-assisted antennae optimizing structure that diminishes training time and enhances converge velocity. A 2G to 5G interior ground station antennae (comprising 40 design parameters and 10 requirements) and a 5G exterior ground station antennae (including 20 design parameters and 15 requirements) are utilized to illustrate the proposed model. The experiments indicate that over 80% of the training duration and around 25% of the repetitions (models and SS) are diminished relative to a state-of-the-art technique while achieving superior antenna efficacy.

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Introduction

Evolutionary Algorithm s (EAs) are extensively utilized in antenna design.[1] Their capacity to escape local optima, independent of the initial layout and characterized by generality, presents advantages in numerous design scenarios. The Differentiated Evolution (DE).[2] and Particle Swarm Optimizing (PSO)[3] methods are undoubtedly at the forefront of evolutionary algorithm-driven antenna development.Given that comprehensive Electromagnetic (EM)[18] calculations are sometimes required to achieve precise efficiency metrics for a prospective design, and EAs typically necessitate tens of thousands of these EM simulations to identify the ideal layout, the optimization process might be excessively lengthy.[4]

Substitute models developed by Machine Learning (ML) approaches are trained to estimate antenna efficiency derived from EM simulations.[5] Numerous computationally intensive EM calculations can be substituted with cost-effective Surrogacy System (SS) forecasts during the optimizing procedure.[19] The optimization duration can be significantly shortened. The study centers on digital SS worldwide optimization of antennas, wherein the SS is continually revised in every repetition.[6]

Three essential aspects for online SS-assisted antenna international optimization are the SS technique, the search managers, and the framework maintenance approach. The SS technique pertains to the fundamental principles of ML and its specialized operators for antennae.Searching operators pertain to the optimization mechanism. The model-based management strategy relates to a structure that facilitates the seamless integration and optimization of the SS.

Given that prediction ambiguity is inevitable, potentially resulting in incorrect integration, the objectives of model administration are to find high-potential alternative models under ambiguity to ensure accurate converging and optimum updates of the SS.The three components are intricately linked. The SS-assisted differentiation for antenna Optimizing Technique (OT) represents a cutting-edge methodology.[7] Empirical evaluations of real antennas demonstrate that OT (first generation) meets design parameters unattainable by DE and PSO, achieving speed enhancements of up to a factor of amplitude over these methods. The SS of OTis further enhanced. Multifidelity and concurrent OTare designed.The novel searching and model administration techniques in concurrent OTachieve an additional speed enhancement of 1.5 to 2 times, excluding the time conserved through parallel EM computations.[24]

A novel ML-based cost-reduced SS-assisted hybridized differentiation technique is introduced for a complicated antenna optimizing model. The proposed system is the inaugural method concentrating on complicated antennas, aiming to diminish the prolonged SS period to an appropriate threshold while preserving superior antenna efficiency.The principal innovations comprise: 1) a self-adaptive GP modeling technique that substantially lowers training expenses while mainly preserving the precision of antenna efficiency predictions and 2) a novel hybrid SS-based antenna optimizing structure that incorporates a cost-effective Radiating Basis Function (RBF) model-assisted local optimization phase into OT. In addition to substituting numerous models, it enhances the converging rate. The advances are comparable with numerous existing methodologies.

Background

As Artificial Intelligence (AI) technology advances, ML methods have exhibited significant efficacy across various domains.[20] In contrast to conventional supervised ML, ML perpetually engages with its surroundings, modifying its actions depending on environmental feedback to progressively identify an ideal decision-making method. Early iterations of AlphaGo employed ML to attain the best possible choices within the extensive solution area of Go.[9]

ML has garnered significant attention in electromagnetic design lately, with SS-based antenna improvement being a crucial component, categorized into offline and online methods. In offline approaches, a high-fidelity SS is initially constructed with few or no modifications to the SS during the optimizing procedure.[8] The benefit of offline techniques is that the resultant practical antenna SS is beneficial in several scenarios, such as antenna circuit co-designing and multi-objective Pareto optimizing, demonstrating exceptional outcomes. Advanced algorithms, such as Fourier subspace-based ML, have recently been developed for EM device simulation and inverse layout, targeting significant bottlenecks.[10]

The constraint for offline algorithms is the "curse of multiplicity."When numerous design factors are present and/or the modeling range is broad, the requisite number of electromagnetic computations to generate adequate training information points for constructing a high-quality SS is substantial, increasing geometrically with the number of influencing parameters.[11] Should ad hoc learning data processing be required, conducting those models consumes significant time, negating the time saved by employing SS. Layout improvements frequently result from advanced antenna SS simulating techniques, or the antenna/electromagnetic device model is predominantly reusable.[15]

ML eliminates manual information labeling and enables entities to adapt their decision-making processes through experimentation and failure in intricate contexts.[12] As a result, particular academics have effectively implemented it in antenna modification.El Misilmaniet al. utilized ML to enable antenna structures to automatically modify their beam path in intricate and constantly evolving settings without human involvement.[21] Wu et al. accomplished real-time modulation of 3-D Multiple Inputs and Multiple Outputs (MIMO) antennae by ML, facilitating the flexible modification of antenna characteristics among various base stations in response to the fluctuation of user transportation, thereby enhancing network accessibility and coverage efficacy.[14] Tedeschiet al. utilized ML systems to enhance satellite array identities, maximizing the device's ability to target several base stations within specified restrictions.[22]

Online approaches continuously enhance the quality of the SS during the optimization procedure.[13] In every repetition, one or more alternative models are constructed with the available modeled option layouts. Search operations produce novel potential layouts determined by the SS.Utilizing the prediction results, candidate solutions with significant potential have been generated to refine the SS for further iterations.[16]. The quality of the SS is not consistently excellent but is progressively enhanced. Initially, the accuracy of the SS is subpar due to insufficient learning data sources.

In contrast to relying on precise SS as in offline approaches, the quality of predictions and associated uncertainty significantly influence the optimizing process.[17]

Inadequate forecasting quality and inadequate consideration of unpredictability significantly increase the likelihood of optimization converging to a local optimum that deviates substantially from the design parameters.[23] Effective integration of the SS technique, search administrators, and model maintenance approach is crucial.

Proposed ML-based self-adaptive antenna optimization model

Antenna Architecture

The preceding section examined the history and research about the suggested high-gain antenna architecture. The following sub-section delineates the analytical methodology for validating the design and variables of the suggested antennae architecture.This section initially discusses the fundamental idea of contemporary approaches, such as the Gaussian Procedure (GP). Examine the findings and where a sample from a Gaussian-distributed chaotic procedure is characterized by its variability and average.Utilizing the k assessments, the Gaussian Process forecasts the value of for the subsequent k; this correlated function is expressed as

$$C(k^a,k^b) = \exp\{-\textstyle\sum_{x=0}^{N-1}\theta_x|k_x^a - k_x^b| * \pi\} \tag{1}$$

The size of u is denoted by N, whereas and are the hyperparameters. The likelihood function is computed as

$$\frac{1}{(2*\pi*\sigma^2)^{\frac{m}{2}}|H|}\exp\left\{-\frac{(r-\mu*K)^T H^{-1}(r-\mu*K)}{2*\sigma^2}\right\} \tag{2}$$

K is a n×1 array, and H is an n×n correlation array.The anticipated value and forecasting ambiguity and are examined as

$$k(r^*)\,H\,(r^{-T}i * K) \tag{3}$$

The ambiguity in predictions is crucial when evaluating the possibilities of user antenna layout.The methods used extensively include preliminary screening, Lower Confidence Bound (LCB), and likelihood.This research introduces the LCB strategy,which utilizes the objective variable with the forecasting probabilities . This is articulated as

$$k_{cd}=y(r^*)-w*S(r) \tag{4}$$

Where w is a constant established for antenna issues in AI methods.The primary disadvantages of GP are its training expenses and substantial computational duration. This work proposes an approach for optimizing antenna layout to address these limitations, including extensive computing time and training costs.Two methods for optimization employed in the creation of antennas are locally optimized and overall optimization. This work uses an integrated optimization strategy for designing antennas via an EA. Each of the population, comprising options is represented by . The donating vector for generating a child response is computed as follows:

$$o^a=x^a+F\{k^{best}-k^a\}+F\{k(m^1)-k(m^2)\} \tag{5}$$

represents the ath matrix in the present , signifies the optimal user option within the present , whereas mutual responses from the sample are arbitrarily chosen.The variable denotes the ath mutual vector, whereas F is the scaling ratio.Figure 1 illustrates the flowchart of the proposed method, delineating the fundamental functions of the Radiating Basis Function (RBF)and LCB methods.

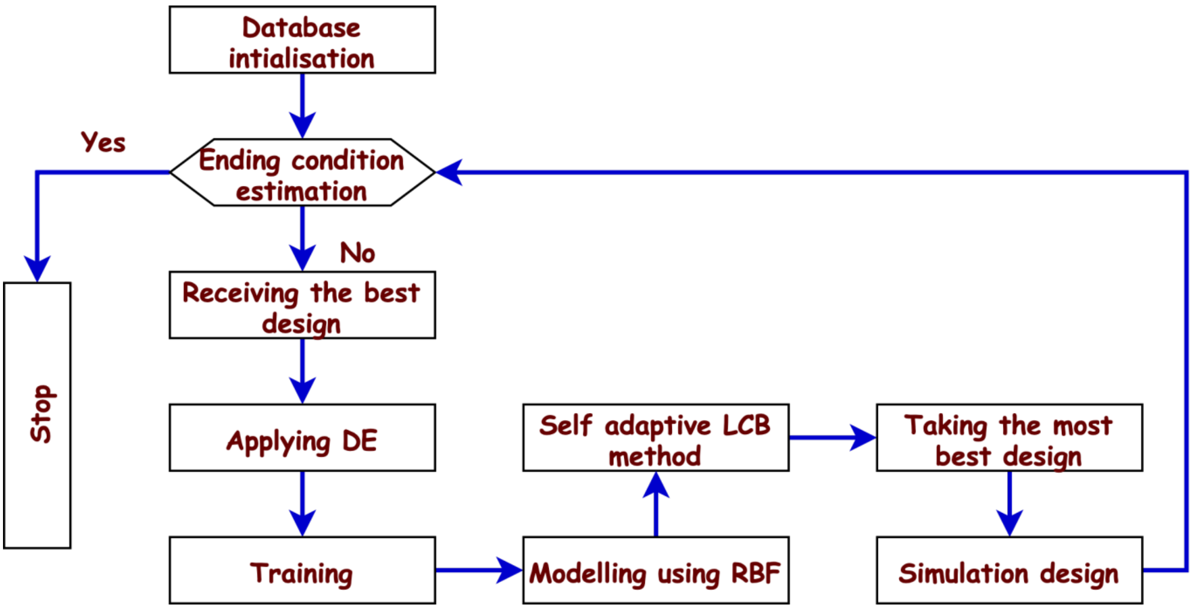

Fig. 1.: Workflow of the proposed model

Algorithm

This research intends to identify a novel ML core to supplant GP and provide an innovative prescreening approach. The proposed technique is anticipated to enhance both the converging rate (i.e., the quantity of EM calculations required to achieve the best design and the learning expense of the SS compared to GP-based methodologies. It ought to apply universally to antenna instances with differing quantities of design factors and requirements.

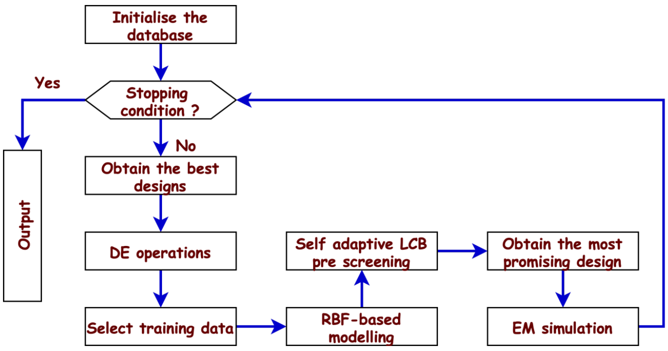

Fig. 2: Flow graph of the algorithm for optimization

The proposed architecture is illustrated in Figure2, and the method operates as follows.

Step 1: Utilize Latin Hypercube Selecting (LHS) to choose a restricted amount of potential layouts from the layout space defined by the Lower Limit (LL) and Upper Limit (UL) of the layout parameters, denoted as . Conduct EM calculations to acquire effectiveness metrics and establish the preliminary databases.

Step 2: If a predetermined stopping condition is satisfied (e.g., the computational budget is depleted or requirements are met), results in the optimal applicant layout from the databases; alternatively, proceed to Step 3.

Step 3: Retrieve the optimal applicant layouts from the dataset to establish a populace P.

Step 4: Utilize the DE/present-to-optimum/1 operation on P to generate new offspring solutions.

Step 5: For every child remedy, acquire the nearest specimens (determined by Euclidean distances) to serve as learning data points and develop anRBF-based SS.

Step 6: Evaluate the child responses produced in Step 4 with the RBF framework and the self-adaptive LCB approach.

Step 7: Execute the EM simulations on the optimally predicted child answer derived from Step 6. Incorporate the assessed candidate layout and associated effectiveness metrics into the dataset.Return to Step 2.

Some model administration operations are derived from conventional OT. This modeling administration approach is garnering significant attention in the AI industry. The two innovative techniques are RBF-based antennae SS (Step 5) and the self-adaptive LCB technique (Step 6). They are interoperable with model administration structures in other OT variants and various online universal optimizing approaches for antennas.

Self-Adaptive LCB Approach

Due to its unique data properties, aprescreening procedure (Step 6) is frequently required for anML core, specifically anRBF-based model. Most current prescreening techniques consider the GP model's data attributes. In the preliminary studies, the commonly employed predicted enhancement and likelihood of enhancement prescreening methods are utilized in conjunction with the RBF-based framework for several antenna scenarios, resulting in over 50% of the trials becoming ensnared in local optimal conditions.This prompts an examination of the disparities in data attributes between RBF and GP regarding projected values and forecast ambiguity to propose a preliminary screening strategy that can escape local optimal and enhance the converging speed for the RBF-based system. It is evident that: 1) regarding the estimated figures, the RBF-based designs and GP-based system are identical, both exhibiting relatively low forecasting error in comparison to the replicated numbers (i.e., ground reality) across all three sample communities and 2) concerning forecasting ambiguity, the RBF-based designs demonstrate significantly lower values than the GP approach, with the disparity becoming more pronounced in the additional iterations.For instance, during the late stages of optimizing, as convergence approaches, the RBF forecasting ambiguity measures 0.1, whereas the GP forecasting ambiguity is 0.5.

Due to insufficient exploration capability, the SS-based antenna universal optimizing method succumbs to local maxima. In optimizing theory, investigation denotes the investigation of the search space that is presently under-informed, whereas exploitation pertains to identifying the best solution inside the well-understood search area.Antenna layout environments are frequently very multimodal, necessitating robust exploration capabilities. Thoroughly accounting for prediction variability is crucial for research, hence the necessity of preliminary screening procedures. In the widely utilized predicted enhancement and possible enhancement preliminary screening approaches, no hyperparameters regulate the research degree, and the anticipated ambiguity derived from the RBF-based model is minimal. Employing anRBF-based model frequently results in convergence to the regional optimal in antenna scenarios, in contrast to utilizing the GP approach.

Results and Findings

This section employs two real-world grounding station antennae to illustrate the suggested approach. The initial example is a 2G to 5G interior ground station antennae comprising 40design factors and 10 requirements. The radiation polarization for interior base station antennae is not strictly necessary for optimum broadside transmission; rather, the antenna must be small and cost-effective. The antenna will encompass the current 2G/3G/4G frequency ranges of 0.7-1.0 and 1.6-2.8 GHz, in addition to the targeted 5G frequency bands of 3.2-3.7 and 4.7-4.9 GHz. The array will demonstrate single-directional radiating structures with an observed gain of at least 5 dB across the entire frequency band. Optimizing an identical antenna using only the OT sequence is challenging due to the excessively lengthy GP calculation duration. The OT is segmented into two phases to minimize the number of design parameters, utilizing ad hoc design expertise.

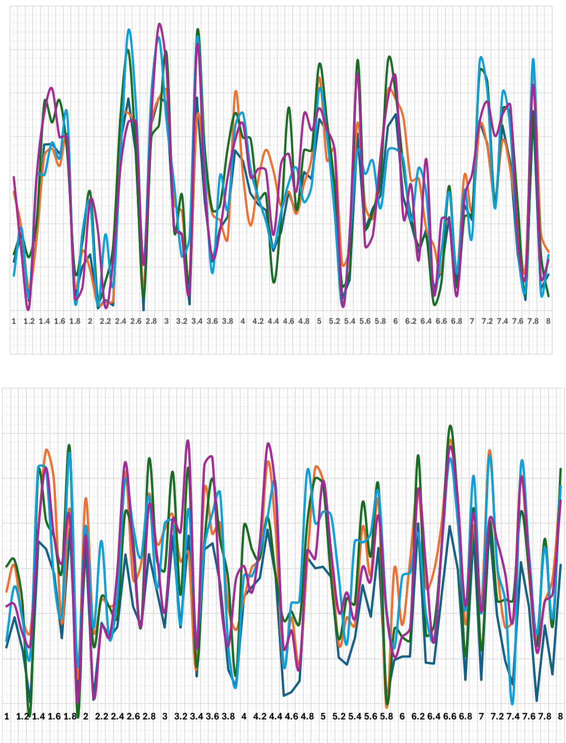

Fig. 3: VSWR and Gain analysis

To assess the robustness, the research examined the optimized Voltage Standing Wave Ratio (VSWR) outcomes and the most significant gain achieved from five test runs. Figure 3(a)depicts the VSWR, revealing that the VSWR outcomes from the five trials exhibit minimal variation, with substantial discrepancies occurring solely between the 4.0-4.9 GHz region; the information curves for the remaining frequency spectrum largely coincide. Figure 3(b) illustrates the highest possible gain, indicating that, exceptfor a notable disparity in Experiment inside the 4.2-5.3 GHz spectrum, the gain variations across the remaining frequency bands are negligible. The evaluation indicates that the framework's resilience presented in this paper is acceptable.

Fig. 4: Reflection factor, Gain, and effectiveness analysis

Figure 4 illustrates a standard optimum design's reflection factor, actual gain, and general effectiveness. As previously indicated, the suggested model has been designated the standard procedure. Across all five trials, it maintains a 100% success rate while utilizing a mean of 2500 EM iterations.The suggested model reduces the number of EM calculations by over 50% relative to conventional OT in the current research, reaffirming its benefits in rapid convergence.

The secondary objective of this case study is to evaluate the costs associated with ML. The proposed OT is suggested for antennas characterized by several design factors and requirements where the modeling duration of GP is an issue.The proposed model frequently decreases the duration of the GP method by 90% through its GP model-sharing technique. For the intended antenna, a median of around 427k GP-basedSS is constructed during the optimization process utilizing the proposed model, requiring approximately 12 hours on the median. This time expenditure is pragmatic yet undesirable. The proposed model's mean learning time for the SS calculated using RBF is 1.5 hours.

The mean data from the five separate trials are utilized. The considerable enhancement in the ML expenses of the proposed model is demonstrated. The overall optimization duration was reduced by almost fifty percent compared to the reference approach. DE is conducted for the 5G antenna. Following two weeks of optimizing, none of the reflection factor criteria are fulfilled, and only fifty percent of the gain and overall effectiveness criteria are achieved. A prolonged run enhances efficiency; the optimization duration is excessively lengthy for practical purposes.This instance confirms the benefits of the proposed model regarding rapid convergence and ML expenses.

Conclusion

The paper proposes a novel training cost-reduction-based SS for a complicated antenna-optimizing model. The effectiveness and productivity of the proposed model are evidenced by its modeling and measuring outcomes of two intricate real-world antennae with demanding specifications for performance, for which no publicly available effective optimization method exists to the current understanding.The self-adaptive GP computing strategy reduces the extensive SS learning time by over 80%, tolerating the entire optimizing duration. The RBF-based local optimizing technique and the new SS-based optimizing approach enhance the convergence pace, resulting in a 25% reduction in GP models and EM computations through inference. The proposed OT model is the inaugural effective way to optimize complicated antennas with numerous design factors and requirements. Future endeavors will encompass the proposed model's behavioral investigation and enhancement.

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