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A Suboptimal Approach to Antenna Design Problems With Kernel Regression

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ABSTRACT This paper proposes a novel iterative algorithm based on a Kernel regression as a suboptimal approach to reliable and efficient antenna optimization. In our approach, the complex and non-linear cost surface calculated from antenna characteristics is fitted into a simple linear model using Kernels, and an argument that minimizes this Kernel regression model is used as a new input to calculate its cost using numerical simulations. This process is repeated by updating coefficients of the Kernel regression model with new entries until meeting the stopping criteria. At every iteration, existing inputs are partitioned into a limited number of clusters to reduce the computational time and resources and to prevent unexpected over-weighted situations. The proposed approach is validated for the Rastrigins function as well as a real engineering problem using an antipodal Vivaldi antenna in comparison with a genetic algorithm. Furthermore, we explore the most appropriate Kernel that minimizes the least-square error when fitting the antenna cost surface. The results demonstrate that the proposed process is suitable to be used in antenna design problems as a reliable approach with a fast convergence time.

INDEX TERMS Antennas, optimization, Kernel regression, cost surface.

I. INTRODUCTION

Recent research topics of antenna engineering often rely on optimization problems to find the best solution in a restricted search space [1]–[3]. The dependency on optimization is much higher for products with short production cycles, such as mobile devices, home appliances, and vehicles, since each individual platform requires additional performance improvements [4], [5]. However, this tuning process requires considerable time and computational resources, especially for an antenna with more design parameters, due to the use of numerical simulations based on complex electromagnetic theories [6]. Furthermore, antenna design problems are usually non-linear and contain a number of local solutions. Thus, there have been a lot of effort to develop more efficient and more reliable optimization algorithms, which are mainly divided into two approaches. The first approach is known as a deterministic method that uses analytic properties of the problem, e.g. gradients [7]. Although this method provides a fast convergence, it has high probability of being trapped in local optima [8]. This issue can be resolved in stochastic approaches, such as simulated annealing [9], [10], swarm algorithms [11]–[13], and evolution strategies [14]–[16], since these methods employ randomness to escape from local solutions. However, the convergence time increases unexpectedly for larger search spaces and is highly dependent on optimization settings [17]. In addition, their solutions are incomprehensible and do not provide any theoretical intuition from antenna engineering standpoints [18].

In this paper, we propose an iterative algorithm based on Kernel regression as a suboptimal approach to reliable and efficient antenna optimization. One of the major contributions is that non-linear cost surfaces of antennas are fitted into simple linear models using Kernel regression [19]. The process begins with initial inputs and corresponding costs obtained

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from numerical simulations to compute the Kernel regression model, whose coefficients are determined by a simple least-square estimator [20]. Then, an argument that minimizes the estimated model is provided as the next input to obtain its cost from another numerical simulation. This new cost is applied for updating coefficients of the Kernel regression model, and the process is repeated until the stopping criteria become true. This means that, at each iteration, the non-linear cost surface is repeatedly translated into an alternative linear function, which can be distinguished from conventional optimization methods that use costs without any post processing. Another major contribution is that existing inputs are partitioned into a limited number of clusters using the K-means clustering algorithm [21]. Advantages of this clustering process are to prevent an over-weighted situation near local optima and to reduce the computational time and resources as the iteration increases. Most importantly, it is more comprehensible compared to stochastic approaches since the relationship between design parameters is inferred from the estimated Kernel regression model (*see* Section IV-B). As a preliminary study, the proposed approach is applied to find the global solution for the Rastrigin function [22], whose number of local optima is easily adjusted by changing the range of input arguments. It is further validated for a real engineering problem using an antipodal Vivaldi antenna in comparison with a genetic algorithm (GA) and a particle swarm optimization (PSO) [23]–[25]. Our validation also includes the study on the most appropriate Kernel for antenna design problems. The results demonstrate that the proposed approach is suitable to reduce the probability of getting stuck in local optima and is as reliable as the GA with a faster convergence time.

II. PROBLEM FORMULATION

It is assumed that an antenna used in this formulation is designed by M design parameters denoted as $\mathbf{x} \in \mathbb{R}^{M\times 1}$, and $\mathcal{X} = \{\mathbf{x}_n | n = 1, 2, \ldots, N\}$ is the feasible set of $\mathbf{x}$ with a finite number of N. The cost surface $y(\mathbf{x})$ is based on antenna characteristics, such as reflection coefficients, mutual coupling, axial ratios, and bore-sight gains, and the antenna design problem that determines $\mathbf{x} \in \mathcal{X}$ minimizing the cost $y(\mathbf{x})$ can be formulated as

$$\mathbf{x}^{\dagger} = \arg\min_{\mathbf{x}\in\mathcal{X}} \quad y(\mathbf{x}). \tag{1}$$

However, in practice, it is very time-consuming and almost impossible to find the optimal solution $\mathbf{x}^{\dagger}$ by searching $y(\mathbf{x})$ for all available $\mathbf{x} \in \mathcal{X}$ due to the non-linearity of $y(\mathbf{x})$. Thus, the problem in (1) is reformulated as a simple linear model based on Kernel regression, which is written by

$$\begin{aligned}\mathbf{y}(\mathcal{X}) &= [y(\mathbf{x}_1), y(\mathbf{x}_2), \ldots, y(\mathbf{x}_N)]^T \\ &\triangleq \mathbf{F}(\mathcal{X}, \mathcal{U})\mathbf{c} + \mathbf{v}(\mathcal{X}).\end{aligned} \tag{2}$$

$\mathbf{y}(\mathcal{X}) \in \mathbb{R}^{N\times 1}$ is the cost vector of $\mathcal{X}$, and $\mathbf{F}(\mathcal{X}, \mathcal{U}) \in \mathbb{R}^{N\times K}$ is the Kernel matrix whose (n, k)-th element is $\mathbf{F}(\mathcal{X}, \mathcal{U})_{(n,k)} = f(\mathbf{x}_n, \mathbf{u}_k)$ with Kernel function $f(\cdot, \cdot)$. $\mathcal{U} = \{\mathbf{u}_k | k = 1, 2, \ldots, K\}$ is a set of centroid vectors, denoted as $\mathbf{u}_k$, that represent centroids of K clusters included in the feasible region $\mathcal{X}$. Our regression model employs the clustered centroids instead of $\mathcal{X}$ to reduce the search space by a factor of N/K for $K \leq N$. The coefficient vector of the model is written by $\mathbf{c} = [c_1, c_2, \ldots, c_K]^T$, and $\mathbf{v}(\mathcal{X}) \in \mathbb{R}^{N\times 1}$ represents uncertainty or mismatch of the model in (2).

Accordingly, the antenna design problem in (1) is translated into an alternative approach given by

$$\hat{\mathbf{x}} = \arg\min_{\mathbf{x}\in\mathcal{X}_i} \quad \mathbf{F}(\mathbf{x}, \mathcal{U})\mathbf{c}. \tag{3}$$

$\mathcal{X}_i \subset \mathcal{X}$ is an effective subset satisfying $|\mathcal{X}_i| \ll |\mathcal{X}|$, where $|\cdot|$ returns the cardinality of a set. To get $\hat{\mathbf{x}}$ close to $\mathbf{x}^{\dagger}$, $\mathcal{U}$ and $\mathbf{c}$ should be determined properly for given $\mathcal{X}_i$ and $\mathbf{y}(\mathcal{X}_i)$. The coefficient vector $\mathbf{c}$ can be simply obtained from the L_2 norm minimization perspective:

$$\hat{\mathbf{c}}(\mathcal{X}_i) = \mathbf{H}(\mathcal{X}_i, \mathcal{U})\mathbf{y}(\mathcal{X}_i) \tag{4}$$

where $\mathbf{H}(\mathcal{X}_i, \mathcal{U}) = \left[\mathbf{F}(\mathcal{X}_i, \mathcal{U})^T\mathbf{F}(\mathcal{X}_i, \mathcal{U})\right]^{-1}\mathbf{F}(\mathcal{X}_i, \mathcal{U})^T$. Then, substituting $\hat{\mathbf{c}}(\mathcal{X}_i)$ for $\mathbf{c}$ in (3) yields

$$\hat{\mathbf{x}} = \arg\min_{\mathbf{x}\in\mathcal{X}_i} \quad \mathbf{F}(\mathbf{x}, \mathcal{U})\mathbf{H}(\mathcal{X}_i, \mathcal{U})\mathbf{y}(\mathcal{X}_i), \tag{5}$$

which indicates that the approach in (3) is interpreted as a suboptimal problem that determines the sets of $\mathcal{X}_i \subset \mathcal{X}$ and $\mathcal{U}$.

TABLE 1. Comparison of the least-square error for the antenna design problem according to various kernels.

Kernels	Equations	LSE
Triangular	$1 - t$	0.25
Parabolic	$\frac{3}{4}(1 - t^2)$	0.42
Biweight	$\frac{15}{16}(1 - t^2)^2$	0.39
Triweight	$\frac{35}{32}(1 - t^2)^3$	0.25
Tricube	$\frac{70}{81}(1 - t^3)^3$	0.07
Gaussian	$\frac{1}{\sqrt{2\pi}}e^{-\frac{t^2}{2\sigma^2}}$	0.19
Cosine	$\frac{\pi}{4}\cos(\frac{\pi}{2}t)$	5.91
Logistic	$\frac{1}{e^t+2+e^{-t}}$	0.20
Sigmoid	$\frac{2}{\pi}\frac{1}{e^t+e^{-t}}$	0.20

III. AN ITERATIVE APPROACH FOR $\mathcal{X}_i$ AND $\mathcal{U}$ WITH K-MEANS CLUSTERING

In this section, we present an iterative algorithm to solve the suboptimal problem with respect to $\mathcal{X}_i$ and $\mathcal{U}$, as described in Table 1. The fundamental idea behind our approach is to find the optimality with a reduced number of numerical simulations for improved efficiency. To give detailed descriptions, let $\mathcal{X}_i$ and $\mathcal{U}_i$ be the sets obtained at the i-th iteration.

At $i = 0$ (*Initialization*), $\mathcal{X}_0$ denotes initial inputs that are randomly selected from $\mathcal{X}$ to initialize the process. Herein, $|\mathcal{X}_0|$ equals N_0, where $N_0 \ll N$ is a predefined value. It is assumed that the resultant vector $\mathbf{y}(\mathcal{X}_0) \in \mathbb{R}^{N_0 \times 1}$ is calculated using numerical simulations, and $\mathcal{U}_0$ is drawn from a uniform distribution within the range of $\mathcal{X}$.

At any $i > 0$ (*Update*), $\mathcal{X}_i$ is updated to include $\hat{\mathbf{x}}_i$, which minimizes the estimated cost with $\mathcal{X}_{i-1}$ and $\mathcal{U}_{i-1}$:

$$\hat{\mathbf{x}}_i = \underset{\mathbf{x} \in \mathcal{X} - \mathcal{X}_{i-1}}{\arg\min} \ \mathbf{F}(\mathbf{x}, \mathcal{U}_{i-1})\mathbf{H}(\mathcal{X}_{i-1}, \mathcal{U}_{i-1})\mathbf{y}(\mathcal{X}_{i-1}). \quad (6)$$

The corresponding cost $y(\hat{\mathbf{x}}_i)$ calculated from the numerical simulation is stacked into the cost vector to be $\mathbf{y}(\mathcal{X}_i) \in \mathbb{R}^{|\mathcal{X}_i| \times 1}$ for $|\mathcal{X}_i| = N_0 + i$. The set $\mathcal{U}_i = \{\mathbf{u}_{k,i} | k = 1, 2, \ldots, K\}$ is updated by the K-means clustering algorithm where $\mathbf{u}_{k,i}$ is the centroid of the k-th cluster $\mathcal{S}_{k,i}$ at the i-th iteration. The partitioning rule is

$$\mathcal{S}_{k,i} = \{\mathbf{x} | \|\mathbf{x} - \mathbf{u}_{k,i-1}\| \leq \|\mathbf{x} - \mathbf{u}_{j,i-1}\|, \mathbf{x} \in \mathcal{X}_i, k \neq j\} \quad (7)$$

for $j = 1, 2, \ldots, K$. Then, $\mathbf{u}_{k,i}$ is calculated with the centroid of $\mathcal{S}_{k,i}$ as follows:

$$\mathbf{u}_{k,i} = \begin{cases} \frac{1}{|\mathcal{S}_{k,i}|} \sum_{\mathbf{x} \in \mathcal{S}_{k,i}} \mathbf{x}, & \text{for } |\mathcal{S}_{k,i}| > 0, \\ \mathbf{u}_{k,i-1}, & \text{for } |\mathcal{S}_{k,i}| = 0. \end{cases} \quad (8)$$

These subsequent procedures are repeated until the stopping criteria meet. The solution to the problem in (3) becomes $\hat{\mathbf{x}}_i$ obtained from (6) at the final iteration.

Algorithm 1 An Iterative Algorithm for $\mathcal{X}_i$ and $\mathcal{U}$

```
    Initialization
    set i ← 0
    draw a random subset X_0 from X
    draw U_0 from a uniform distribution over [x_min, x_max]
    obtain y(X_0) via numerical simulations
    Update
    set i ← i + 1
    find x̂_i in (6)
    update X_i = X_{i-1} ∪ {x̂_i}
    obtain y(x̂_i) via numerical simulations
    determine S_{k,i}, ∀k in (7)
    compute u_{k,i}, ∀k in (8)
    if stopping criteria = true then
        stop and return x̂_i
    end if
    go to Update and repeat
```

IV. VALIDATION IN LOCAL OPTIMA PROBLEMS

A. RASTRIGIN FUNCTION

The Rastrigin function is a non-linear problem that is often used to validate effectiveness of optimization algorithms. The function exhibits a complex cost surface with many local optima and is written by

$$g(\mathbf{x}) = 10M + \sum_{m=1}^{M} [x_m^2 - 10\cos(2\pi x_m)]. \quad (9)$$

x_m is the m-th argument of the input vector $\mathbf{x}_n \in \mathcal{X}$, and the range of $\mathbf{x}$ is assumed as $[-2,2]$. In this assumption, the search space includes 25 local optima, and the global optimum with a value of zero is located at $\mathbf{x} = 0$. Note that the number of local optima represents the difficulty of optimization problems, which can be easily adjusted by varying the range. In this validation, M is limited to two for illustrating 2-D cost surfaces, and a Gaussian Kernel is employed for the proposed regression model in (2).

Fig. 1a presents an example cost surface with 30 inputs that are specified by '×' markers. This cost surface is calculated from the estimated regression model, and we can find next input arguments from the minimum value of the surface, as shown by a red '∗' marker. Then, we compute the real cost value of these input arguments by solving the Rastrigin function, and the cost surface is recalculated by including the input arguments and its corresponding cost. This update process is recursively repeated until meeting the stopping criteria, which implies that the data size increases in every iteration. Thus, when the input data are biased toward a certain point, the optimization process might face into an over-weighted situation near a local optimum as illustrated in Fig. 1b. In this case, the estimated model is not able to escape from the local point, and its next input arguments remain in a nearby area. Therefore, the K-means clustering algorithm plays a key role to achieve more reliable results by clustering, in a sense of spreading, the input data within a search space. Another advantage of using this algorithm is that the total number of inputs reduces to the number of clusters, K, which allows for lower computational complexity. Fig. 1c shows an estimated cost surface with 300 inputs that are well-distributed based on K centroids specified by red squares. In addition, as anticipated, the fitted surface is similar to the actual Rastrigin function, and the global optimum is found at $\mathbf{x} = 0$.

B. ANTENNA DESIGN PROBLEM

The proposed algorithm is now validated for a real antenna design problem. In this section, a commercial full-wave electromagnetic simulator, FEKO [26], is used to calculate the cost, and the information of calculated costs is used to find the next input arguments based on the proposed suboptimal approach. Fig. 2 shows a geometry of an antipodal Vivaldi antenna that is often adopted for a broad-band application. The antenna consists of upper and lower ridges that are placed on different sides of a thin substrate having length l_{ant} and width w_{ant}. Outer edges at the top and bottom ends have length l_{ridge}, and the shape of inner edges flares based on a function, f_{ridge}, defined by

$$f_{ridge}(p) = 0.01 \cdot \exp(0.003 \cdot s_{ridge} \cdot p). \quad (10)$$

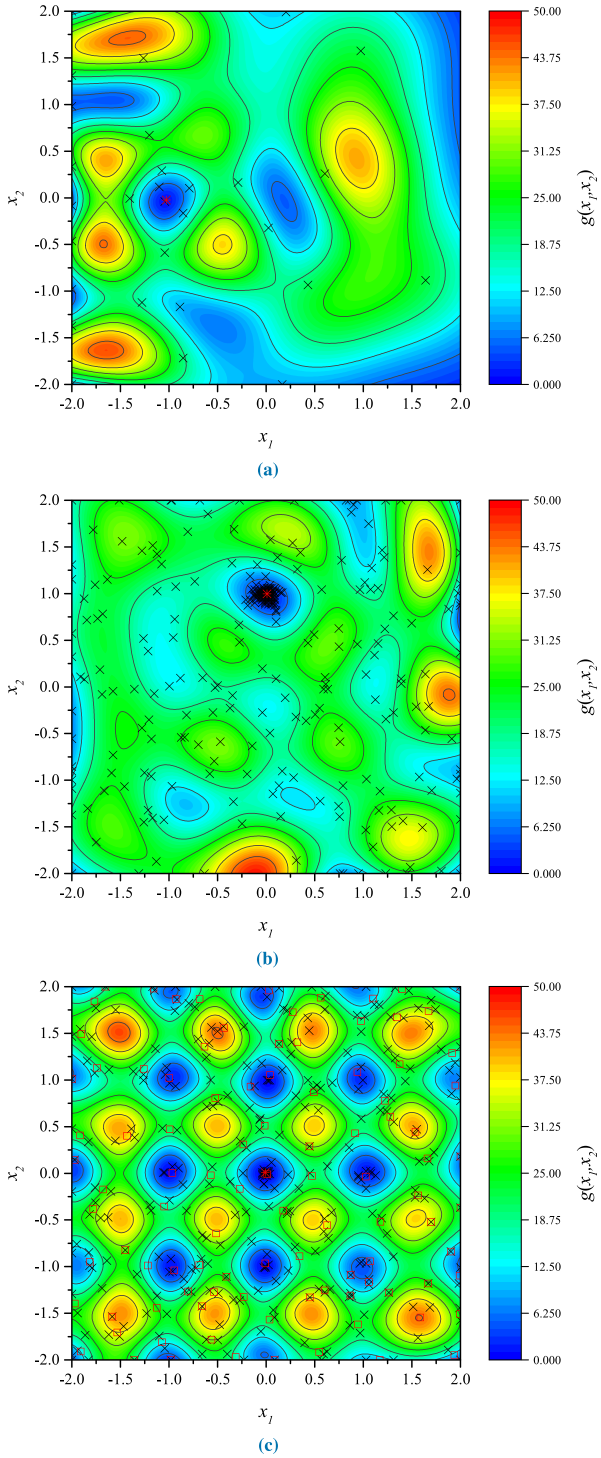


FIGURE 1. Example cost surfaces of the Rastrigin's function. The proposed approach has a lower probability of pointing local solutions due to the *K*-means clustering algorithm. (a) Under-fitted surface (30 inputs). (b) Over-weighted surface near a local optimum (300 inputs). (c) Fitted surface with well-distributed 300 inputs using the *K*-means clustering algorithm.

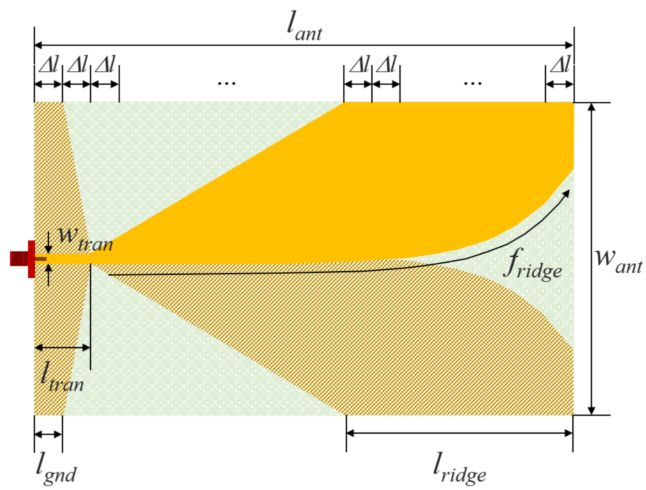


FIGURE 2. Geometry of an antipodal Vivaldi antenna used as an example of the real design problem to verify the feasibility. To present a 2-D cost surface, only two key design parameters are optimized by the proposed algorithm.

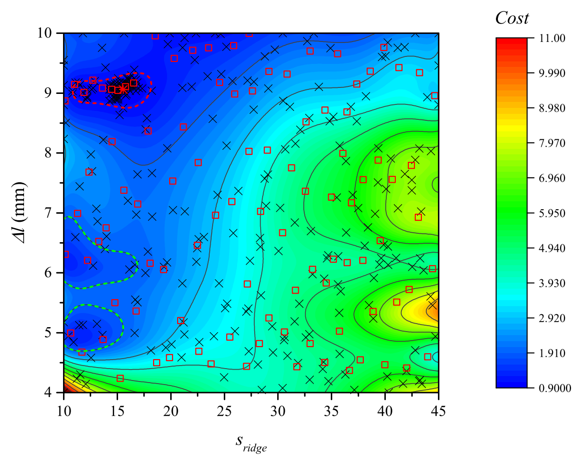


FIGURE 3. Predicted cost surface of the antipodal Vivaldi antenna. This visualized cost surface gives additional knowledge of relationships between design parameters under test.

s_{ridge} represents the slope of the edges, and p is an input argument. These ridges are then connected to the transition part that contains the ground with an edge length of l_{gnd} and a thin microstrip line whose design parameters are width w_{tran} and length l_{tran}. It is assumed that longitudinal parameters are proportional to unit length Δl to reduce the dimension of search spaces, e.g. $l_{ant} = 19 \cdot \Delta l$, $l_{ridge} = 8 \cdot \Delta l$, $l_{tran} = 2 \cdot \Delta l$, and $l_{gnd} = 1 \cdot \Delta l$.

In our optimization, Δl has a range from 4 mm to 10 mm, and s_{ridge} varies between 10 and 45, which includes from almost linear to extremely steep shapes. At each iteration, bore-sight gains are calculated using the numerical simulation in the frequency band between 1 GHz and 6 GHz at intervals of 50 MHz. Then, the reciprocal of the minimum bore-sight gain is defined as the optimization cost. The stopping criteria of the iterative process are: (i) the number of iterations reaches to the maximum iteration of 300; (ii) the cost is less than 0.5 ($\geq +3$ dBi); (iii) the least-square error (LSE) of fitting the cost surface becomes greater than 0.1; (iv) the optimization process produces duplicated $\hat{\mathbf{x}}_i$ more than five straight times. The K-means clustering process is activated when the number of input data, N, is greater than 100.

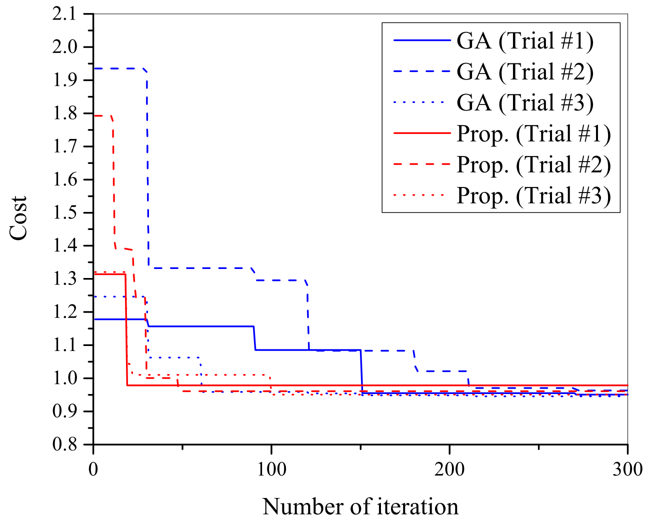


FIGURE 4. Variations of costs according to the number of iterations. For a fair comparison, three independent trials are conducted for both approaches.

TABLE 2. Comparison of the least-square error for the antenna design problem according to various kernels.

Parameters	Values
s_{ridge}	15.56
Δl	9.06 mm
l_{ant}	172.14 mm
l_{ridge}	72.48 mm
l_{tran}	18.12 mm
l_{gnd}	9.06 mm
w_{ant}	100 mm
w_{tran}	2.5 mm

To conduct in-depth studies on finding the most appropriate Kernel for antenna design problems, independent optimizations are executed using nine different Kernels. Table 1 lists detailed equations with their average LSEs, where $t = \|\mathcal{X} - \mathcal{U}\|$. As can be seen, the Tricube Kernel is superior to other Kernels with the LSE of 0.07, and another possible candidate is the Gaussian Kernel with the second lowest LSE of 0.19. Fig. 3 illustrates the estimated cost surface using the Tricube Kernel, and the contours represent levels of cost values. The area near the global optimum is specified by a red dotted line, in which has the most dense distribution of the inputs specified by '$\times$' markers. As can be seen, the centroids of clusters, marked as red squares, are uniformly distributed within the search space, which helps to prevent getting stuck in local optima specified by green contours. Another important aspect to point out is that we can learn relationships between design parameters from the estimated cost surface. For example, when the slope of inner edges are steeper than $s_{ridge} \geq 30$, Δl should be greater than 9.7 mm to maintain the cost less than 2 ($cost \geq -3$ dB).

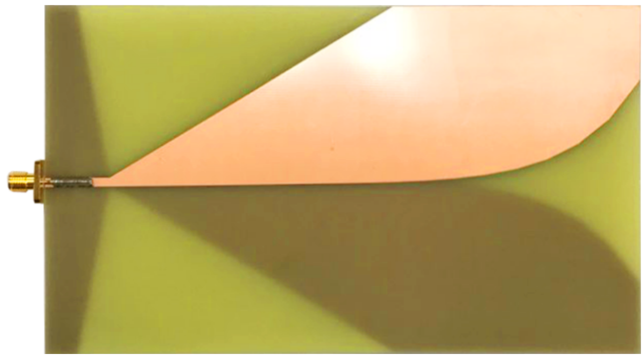


FIGURE 5. Photograph of the fabricated antenna. The conducting surface on the other side of the FR4 substrate is projected as a darker area.

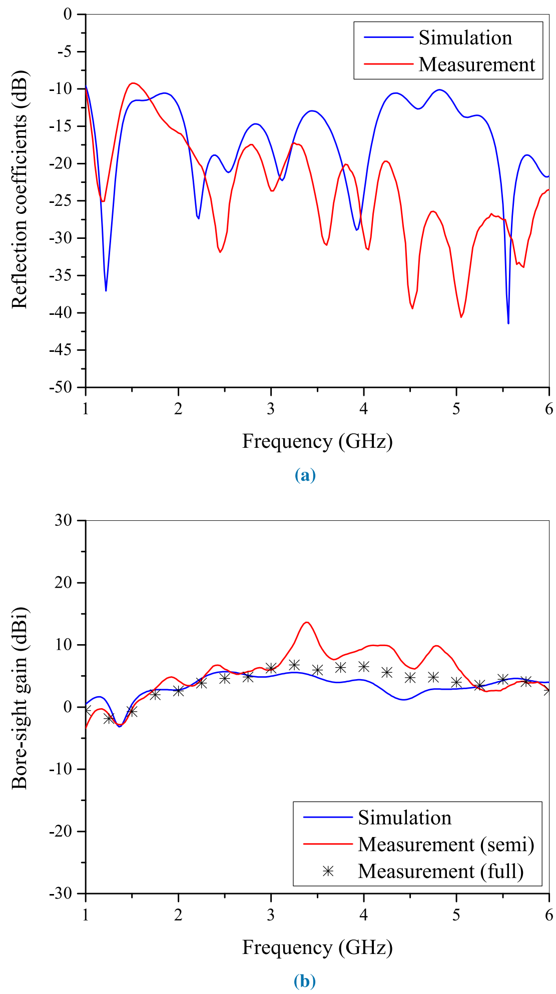
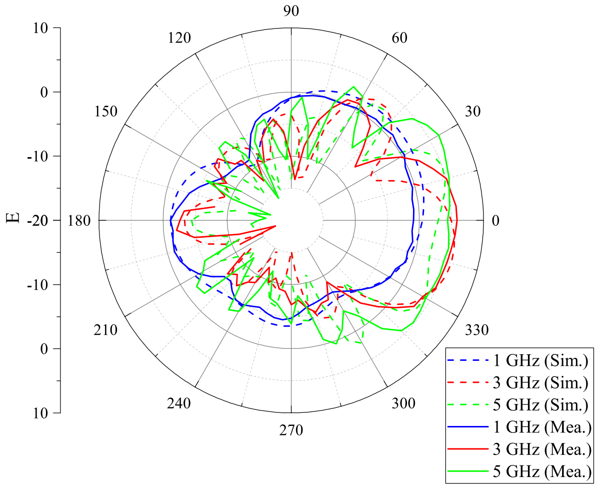
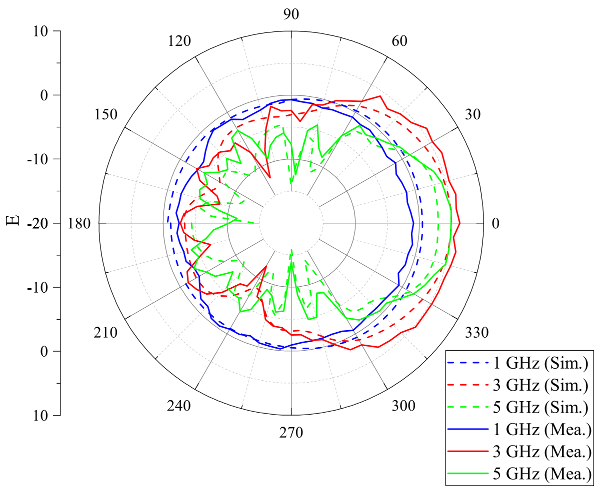


FIGURE 6. Example cost surfaces of the Rastrigin's function. The proposed approach has a lower probability of pointing local solutions due to the *K*-means clustering algorithm. (a) Reflection coefficients. (b) Bore-sight gain.



(a)



(b)

FIGURE 7. Measured radiation patterns of the fabricated antenna in comparison with simulated results. (a) *z*-*x* plane. (b) *x*-*y* plane.

Fig. 4 shows cost variations in comparison with the GA according to the number of iterations. It is assumed that each generation of the GA contains 30 populations, and chromosomes obtained from the top 33% are used for reproduction. Note that the cross-over and mutation rates are 0.8 and 0.1, respectively. Since the convergence behaviors of both approaches are affected by initial inputs, three independent optimizations were executed, as specified by solid, dashed, and dotted lines. The results confirm that the proposed approach tends to converge faster, and its optimized costs are as low as the GA. Table 2 lists design parameters of the minimum cost that is indicated by the red '$*$' marker. Fig. 5 shows a photograph of the optimized antenna fabricated on an FR4 substrate ($\epsilon_r = 4.5$, tan$\delta = 0.02$) with a thickness of 1.6 mm, and the darker area indicates the conducting surface on the other side of the substrate.

Fig. 6a presents measured reflection coefficients in comparison with simulated data. Both results show a good agreement and maintain the values less than -10 dB in the entire frequency range. We also measured the bore-sight gain as shown in Fig. 6b, and the data obtained from a full anechoic chamber are specified by black '$*$' markers. The minimum and maximum gains are -1.87 dBi and 6.79 dBi at 1.25 GHz and 3.25 GHz, respectively, which exhibits that the gain is almost flat with a deviation of 8.66 dB.

Fig. 7a shows simulated and measured radiation patterns in the z-x plane at 1 GHz, 3 GHz, and 5 GHz. Half-power beamwidths (HPBWs) of the simulated results are 109.7°, 43.8°, and 70.2°, and those of the measured data are 129.8°, 58.4°, and 88.1°. Fig. 7b presents measured patterns in the x-y plane in comparison with the simulation. Both results tend to be more directive toward $\phi = 0°$ as the frequency increases, for instance, measured HPBWs are 293.9° (1 GHz), 113.2° (3 GHz), and 56.5° (5 GHz). The results confirm that the optimized antenna is feasible for broad-band applications, and the proposed algorithm is as efficient as the GA for real antenna design problems. Note that the proposed algorithm can also be applied for any type of antennas, e.g. microstrip patch antennas, wire antennas, and aperture antennas, and there are three considerations that should be carefully determined before initiating the optimization process: design parameters of interests, parameter ranges and intervals, cost functions.

TABLE 3. Comparison of optimized results and the number of iterations for the optimum cost.

Results	Proposed	PSO	GA
Min. cost	0.9458	0.9573	0.9604
Iteration	211/300	271/300	238/300
s_{ridge}	15.56 mm	16.75 mm	15.72 mm
Δl	9.06 mm	9.06 mm	9.10 mm
Max. $\lvert S_{11}\rvert$	–9.56 dB	–6.94 dB	–6.01 dB
Avg. $\lvert S_{11}\rvert$	–16.87 dB	–13.62 dB	–14.07 dB
Avg. gain	3.41 dBi	2.44 dBi	2.52 dBi
Min. gain	–3.17 dBi	–3.33 dBi	–3.45 dBi

C. VALIDATION WITH COMMERCIAL OPTIMIZERS

The proposed algorithm is now validated in comparison with other optimization processes, such as PSO and GA, that are currently available in a commercial simulator [26]. For a fair comparison, the maximum number of iterations is restricted to 300, and default settings are employed for optimization conditions. In addition, the same cost function is adopted to maximize the bore-sight gain within the frequency range between 1 GHz and 6 GHz, which is identical to the previous sections. Table 3 shows comparisons of the optimized results for the commercial optimizers. Achievable minimum costs of the proposed method, PSO, and GA are 0.9458, 0.9573, and 0.9604, respectively, and these values are obtained at 211^{th}, 271^{st}, and 238^{th} iterations. The results support that the proposed method is capable of more efficient optimization with less computational efforts compared to other commercial optimizers. In addition, reflection coefficients and bore-sight gains obtained from the proposed algorithm are consistently better within the target frequency band.

V. CONCLUSION

We investigated the novel approach to antenna optimization based on Kernel regression. The major contribution is to replace the complex and non-linear cost surfaces to simple linear models by determining model coefficients. The K-means clustering algorithm was employed to prevent the over-weighted situation near local optima and to avoid significant increase of computational time and resources by partitioning existing inputs into a limited number of clusters. Another important aspect is that the fitted cost surface provides comprehensible knowledge from the relationship between design parameters. In the antenna optimization, the tricube Kernel presented the lowest LSE of fitting the cost surface, and the proposed approach showed faster convergence times compared to the GA. The optimized antenna exhibited broad-band characteristics with reflection coefficients of less than -10 dB in the entire frequency band, and the bore-sight gain was greater than -1.87 dBi with a gain deviation of 8.77 dB. The results confirmed that the proposed approach is suitable to achieve reliable designs in antenna applications with a fast convergence time.

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