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Surrogate Modeling Framework for Cost-Effective and Efficient Design of Dielectric Resonator Antennas in Wireless Communication Systems

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Abstract—This paper presents a surrogate-assisted optimization framework for dielectric resonator antennas (DRAs) operating at 24 GHz, targeting fast impedance matching through automated electromagnetic (EM) simulations and deep neural network (DNN) modeling. Two DRA geometries are investigated: a rectangular DRA (RDRA) and a cylindrical DRA (CDRA). For each geometry, two dielectric constants are considered ($\epsilon_r = 10$ and $\epsilon_r = 79$), resulting in four design cases. A CST Studio Suite time-domain EM solver is coupled with Python (CST interface) and MATLAB to generate training datasets over a wide frequency window (18–30 GHz). A DNN surrogate is trained to learn the mapping from key physical design variables (DRA dimensions, substrate size parameters, probe insertion depth, and feed offset location) to the matching objective. Bayesian optimization is then performed on the learned surrogate to rapidly identify candidate designs with minimized $|S_{11}|$ near 24 GHz. The results indicate that high-permittivity DRAs tend to require increased EM simulation time compared to moderate-permittivity DRAs due to shorter effective wavelength inside the resonator and tighter numerical discretization demands. The proposed workflow enables significant reduction in iterative design time and provides a scalable pathway to extend optimization toward multi-objective constraints and larger configurations such as DRA-MIMO systems.

Index Terms—Dielectric resonator antenna (DRA), rectangular DRA, cylindrical DRA, 24 GHz, surrogate modeling, deep neural networks, Bayesian optimization, automation.

I. INTRODUCTION

Dielectric resonator antennas (DRAs) are attractive for mmWave biomedical links because they can be compact, radiate stably, and avoid excessive conductor loss compared with many planar radiators, while still allowing probe excitation and packaging [1]–[3]. The practical difficulty is that DRA tuning is not a single-parameter exercise. Even for a basic probed structure, the resonance location and impedance match are coupled to the DRA dimensions, finite substrate/ground

size, and the feed configuration (offset and insertion depth). As the number of tunable variables increases, dense parameter sweeps or repeated manual tuning in a full-wave solver quickly becomes time consuming.

This paper proposes a surrogate-assisted workflow that automates CST simulations using MATLAB and Python, trains a compact deep neural network (DNN) surrogate, and then applies Bayesian optimization to identify a parameter set that minimizes reflection near 24 GHz. Four cases are studied at 24 GHz: RDRA and CDRA, each evaluated with Eccostock Hik ceramic ($\epsilon_r = 10$) and TiO_2 ceramic ($\epsilon_r = 79$) as the DRA material and Rogers RT/duroid 5880 ($\epsilon_r = 2.2$) as the substrate. Higher- ϵ_r cases generally require more solver effort due to smaller electrical wavelength and tighter discretization demands, while mesh refinement further increases runtime; therefore training samples are generated with default meshing and only final verification is repeated with local refinement [4]. The overall surrogate-assisted design and optimization workflow is summarized in Fig. 1.

II. SURROGATE-ASSISTED FRAMEWORK (CST–MATLAB–PYTHON)

A. Software setup and automation

CST Studio Suite® 2025 is used as the full-wave EM solver. MATLAB® manages the experiment loop (parameter lists, calls, timing, and logging), while Python (CST interface API) opens the CST project, updates parameters, rebuilds the model, runs the solver, and exports the full $S_{11}(f)$ response to text files [4]–[6]. In this work, training samples are generated over a broad frequency span (18–30 GHz). Using a wider window helps the surrogate see multiple resonances and coupling regimes instead of learning only a narrow local behavior around 24 GHz, which tends to reduce brittle predictions near the parameter bounds. The complete CST–Python–MATLAB

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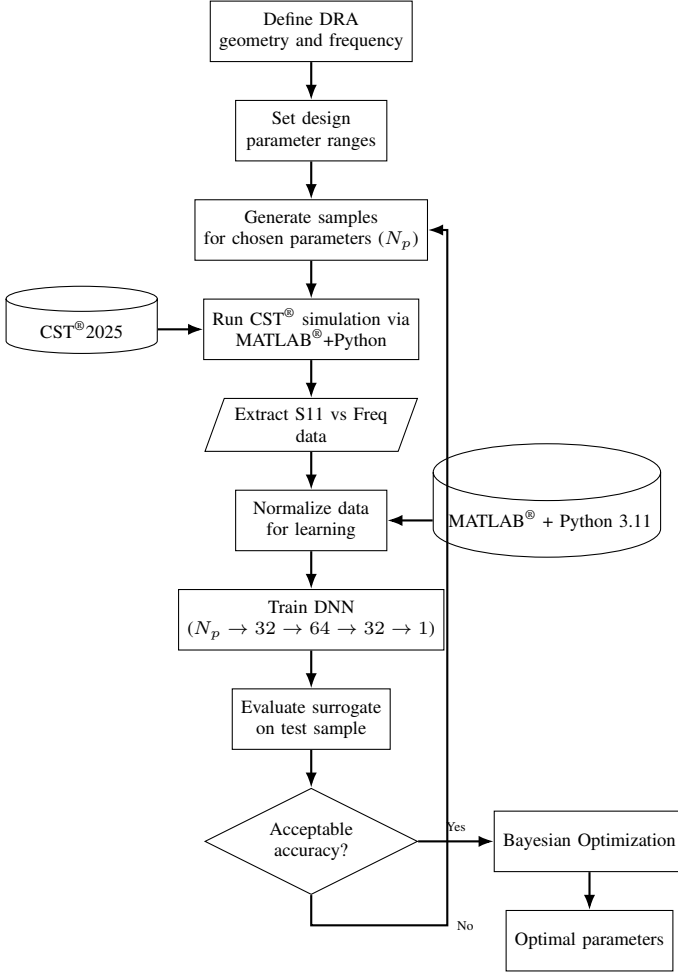


Fig. 1. Surrogate modeling and optimization framework for DRA design

automation and surrogate learning pipeline is illustrated in Fig. 2.

B. Learning objective and labels

For each parameter vector $\mathbf{x}$, CST provides a discrete frequency sweep $S_{11}(f_k; \mathbf{x})$ exported from the 1D results. A direct matching objective at $f_0 = 24$ GHz can be written as

$$J(\mathbf{x}) = |S_{11}(f_0; \mathbf{x})|_{\text{dB}}, \quad f_0 = 24 \text{ GHz}, \quad (1)$$

where $S_{11}(f_0; \mathbf{x})$ is obtained either by selecting the nearest simulated frequency point or by a simple linear interpolation between adjacent samples. In practice, the resonance can shift slightly across the design space, so using a narrow-band minimum provides a more stable label:

$$J(\mathbf{x}) = \min_{f \in [f_0 - \Delta f, f_0 + \Delta f]} |S_{11}(f; \mathbf{x})|_{\text{dB}}, \quad (2)$$

with Δf typically set to 0.1–0.3 GHz depending on the desired tolerance around 24 GHz. In this paper, the reported optimization is centered on minimizing reflection at 24 GHz, and the same extracted $S_{11}(f)$ curves are also used for final

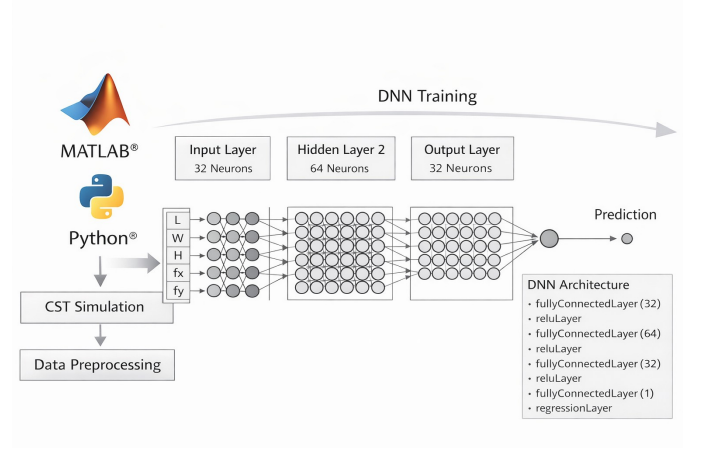


Fig. 2. CST–Python–MATLAB automation and DNN surrogate structure used for learning and prediction.

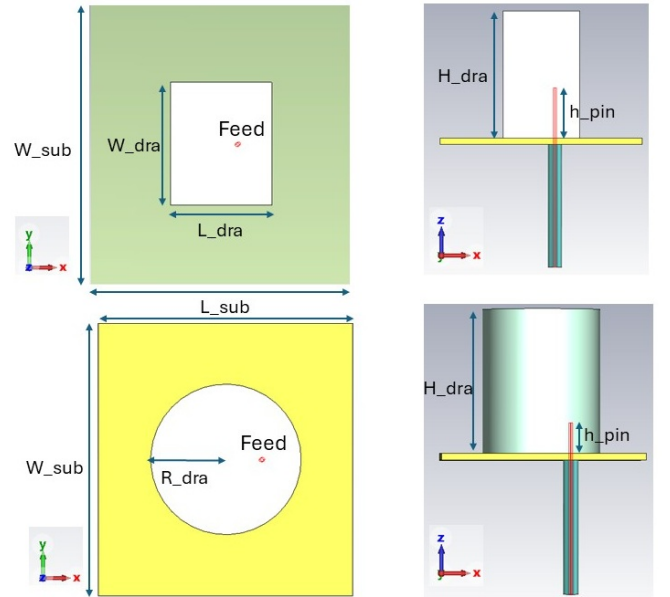


Fig. 3. Geometry and parameter definitions for RDRA (top) and CDRA (bottom), including probe insertion depth h_{pin} and feed offsets.

CST verification plots. This formulation allows the surrogate to remain robust even when the resonance shifts slightly with geometry, which is common in probe-fed DRAs.

C. DNN surrogate architecture and training

A feedforward regression DNN is trained to approximate $J(\mathbf{x})$ from the selected geometry and feed variables. The input dimension equals the number of tuned parameters for the considered case (e.g., RDRA uses $(L_{\text{dra}}, W_{\text{dra}}, H_{\text{dra}})$ in the basic sweep, while extended runs can append $(L_{\text{sub}}, W_{\text{sub}}, h_{\text{pin}}, \text{feedoff}_x, \text{feedoff}_y)$). For consistency across cases, the same compact hidden-layer template is used (32–64–32 neurons with ReLU activations and a scalar regression output) [7], [8].

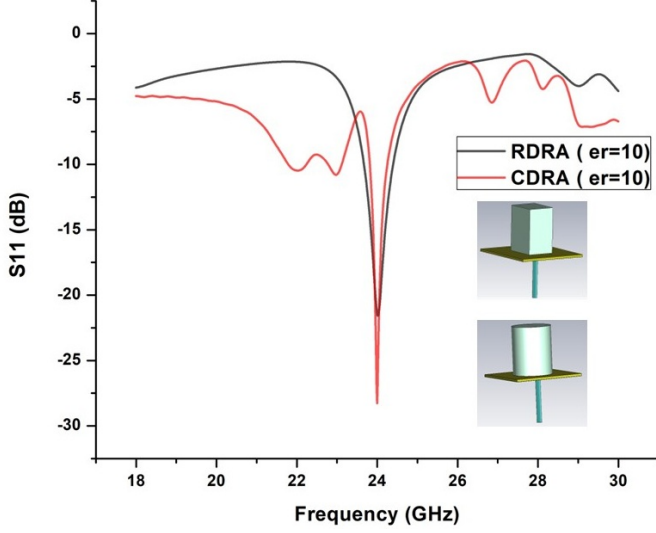


Fig. 4. S_{11} comparison for RDRA and CDRA with $\epsilon_r = 10$

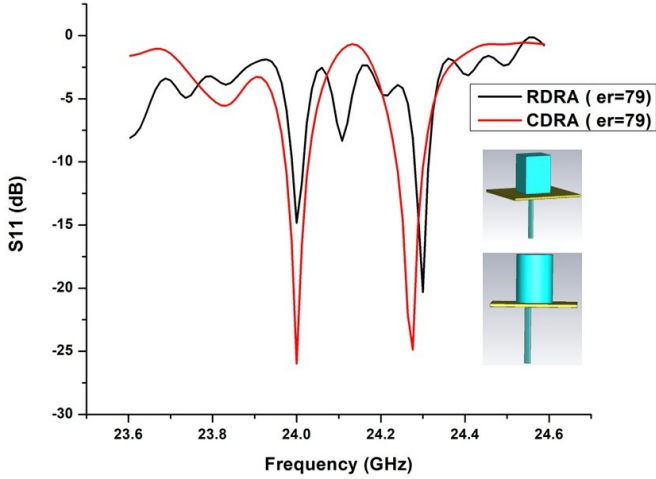


Fig. 5. S_{11} comparison for RDRA and CDRA with $\epsilon_r = 79$

Before training, features are normalized to avoid scale bias between geometric parameters (mm) and offsets:

$$\mathbf{x}_n = \frac{\mathbf{x} - \boldsymbol{\mu}}{\boldsymbol{\sigma}}, \quad (3)$$

where $\boldsymbol{\mu}$ and $\boldsymbol{\sigma}$ are computed from the training set. Training is performed in MATLAB using Adam with mean-squared error loss; a small minibatch is used since the dataset size is limited. A held-out validation split is used to check overfitting, and once the validation error stabilizes the trained surrogate is passed to Bayesian optimization.

D. Surrogate-based Bayesian optimization and time saving metric

After training, the DNN surrogate is embedded within a Bayesian optimization loop to explore the bounded design space efficiently. An expected-improvement acquisition

function is employed to balance exploration and exploitation while avoiding repeated full-wave evaluations [9], [10]. The final candidate predicted by the surrogate is then validated using a full CST simulation. For high-permittivity designs ($\epsilon_r = 79$), the simulated S_{11} responses show two nearby notches around the operating band (dual resonance), which indicates coupling to adjacent modes. In practice, the lateral feed offset ($\text{feedoff}_x, \text{feedoff}_y$) and probe insertion depth h_{pin} provide the strongest control over coupling strength and mode selection, and are therefore the first tuning variables used to shift or merge these resonances toward 24 GHz [3].

To quantify the computational benefit, the total time saving is expressed as

$$\eta(\%) = 100 \left(1 - \frac{T_{\text{train-sim}} + T_{\text{DNN}} + T_{\text{BO}}}{T_{\text{ref}}} \right), \quad (4)$$

where $T_{\text{train-sim}}$ is the cumulative CST time used to generate the training dataset, T_{DNN} is the MATLAB-based DNN training time, and T_{BO} is the surrogate-only Bayesian optimization runtime. The reference cost T_{ref} is defined as the runtime of a conventional solver-in-the-loop search with a fixed evaluation budget,

$$T_{\text{ref}} \triangleq N_{\text{ref}} \bar{T}_{\text{sim}}, \quad \bar{T}_{\text{sim}} = \frac{T_{\text{train-sim}}}{N_{\text{train}}}, \quad N_{\text{ref}} = 1000, \quad (5)$$

so T_{ref} scales with the measured average CST time per evaluation for the same antenna case.

III. ANTENNA DESIGN CASES AND RESULTS ANALYSIS

Two probe-fed dielectric resonator antenna geometries are investigated at 24 GHz. The rectangular DRA (RDRA) is parameterized by $(L_{\text{dra}}, W_{\text{dra}}, H_{\text{dra}})$, while the cylindrical DRA (CDRA) is defined by $(R_{\text{dra}}, H_{\text{dra}})$. In both cases, finite substrate dimensions $(L_{\text{sub}}, W_{\text{sub}})$ are explicitly included because the ground-substrate extent influences impedance behavior and modal coupling at mmWave frequencies; a Rogers RT/duroid 5880 substrate ($\epsilon_r = 2.2$) with 0.3 mm thickness is used throughout this study. The feed configuration is controlled by the lateral offsets ($\text{feedoff}_x, \text{feedoff}_y$) and the probe insertion depth h_{pin} , which acts as a strong matching lever by directly adjusting the external coupling and effective Q of the excited mode [2], [3]. The corresponding geometries and design parameters for RDRA and CDRA are illustrated in Fig. 3.

Table I summarizes the surrogate-assisted optimization results for the four design cases (RDRA and CDRA with $\epsilon_r = 10$ and $\epsilon_r = 79$). A clear trend is observed in the total CST simulation time: high-permittivity designs ($\epsilon_r = 79$) require significantly longer runtimes than their $\epsilon_r = 10$ counterparts, which is consistent with the reduced wavelength inside the dielectric and the resulting need for finer numerical discretization. This behavior is reflected in both RDRA and CDRA configurations.

The corresponding S_{11} responses in Fig. 4 and Fig. 5 show that, for $\epsilon_r = 10$, both RDRA and CDRA exhibit a single dominant resonance that can be aligned close to 24 GHz through

TABLE I
SURROGATE-ASSISTED OPTIMIZATION RESULTS FOR RDRA AND CDRA AT 24 GHz

Antenna Type	Relative Permittivity (ϵ_r)	Training Samples	Total CST Simulation Time, $T_{\text{train-sim}}$ (s)	MATLAB DNN Training Time T_{DNN} (s)	BayesOpt Time T_{BO} (s)	Total Time Saving (%)	Best Predicted Parameters (mm)
RDRA	79	100	970 759	30.09	11.67	92.6	$L=3.05$, $W=3.71$, $H=5.05$, $\text{feed_off}_x=0.6678$, $\text{feed_off}_y=0$, $h_{\text{pin}}=2.121$, $L_{\text{sub}}=9.71$, $W_{\text{sub}}=9.05$
RDRA	10	100	147 425	30.17	10.52	91.9	$L=3.73$, $W=4.54$, $H=6.19$, $\text{feedoff}_x=0.66$, $\text{feedoff}_y=0$, $h_{\text{pin}}=2.476$, $L_{\text{sub}}=10.54$, $W_{\text{sub}}=9.73$
CDRA	79	100	952 538	31.23	12.36	93.0	$H=5.05$, $R=1.94$, $\text{feed_off}_x=0.66$, $\text{feed_off}_y=0$, $h_{\text{pin}}=2.02$, $L_{\text{sub}}=9.88$, $W_{\text{sub}}=9.88$
CDRA	10	100	134 806	29.38	10.46	92.3	$H=6.43$, $R=2.63$, $\text{feed_off}_x=1.315$, $\text{feed_off}_y=0$, $h_{\text{pin}}=1.363$, $L_{\text{sub}}=11.26$, $W_{\text{sub}}=11.26$

moderate adjustments of the feed offset and probe insertion depth. In contrast, the $\epsilon_r = 79$ cases (Fig. 5) frequently exhibit two closely spaced notches near the operating band, indicating excitation of adjacent resonant modes. In these cases, the relative depth and spacing of the notches are strongly influenced by $(\text{feedoff}_x, \text{feedoff}_y)$ and h_{pin} , and careful tuning of these parameters allows the dominant resonance to be shifted or merged toward the target frequency.

Overall, the parameter sets reported in Table I should be interpreted as high-quality starting points rather than final designs. In practice, once a surrogate-selected candidate is identified, a short CST verification loop with localized mesh refinement around the probe tip and dielectric boundaries is sufficient to compensate for small frequency shifts and to sharpen the impedance match without re-entering a full optimization cycle [4].

IV. CONCLUSION

A CST–MATLAB–Python surrogate-assisted workflow was demonstrated for rapid impedance matching of probe-fed RDRA and CDRA designs at 24 GHz, covering two dielectric constants ($\epsilon_r = 10$ and 79) and therefore four cases. The method reduces dependence on large solver-in-the-loop searches by training a compact DNN surrogate from a limited number of full-wave samples and then applying Bayesian optimization on the surrogate to propose a candidate design [7], [9], [10]. The higher- ϵ_r cases tend to be more sensitive and can show nearby resonant features; feed offset and insertion depth are effective knobs to control coupling and align the dominant notch to 24 GHz [3].

The same framework can be extended with little structural change to multi-objective constraints (e.g., gain limits, radiation efficiency, bandwidth) and to higher-dimensional layouts such as arrays and DRA-MIMO, where brute-force simulation becomes prohibitive. A practical next improvement is adaptive sampling (active learning), adding new CST points only where the surrogate error or uncertainty is high, rather than sampling uniformly across the full parameter bounds [10], [11].

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