

Article

Inverse Design of Ultra-Wideband Microstrip Filters Based on Conditional Diffusion Networks

Rongzhen Xu ^{1,2}, Zhongfang Ren ^{1,2}, Haoshun Zhang ^{1,2} and Haipeng Wang ^{1,2,3,*} 

¹ School of Electronics & Information Engineering, Nanjing University of Information Science and Technology, Nanjing 210044, China; 202383270254@nuist.edu.cn (R.X.); 202312490409@nuist.edu.cn (Z.R.); 202412490657@nuist.edu.cn (H.Z.)

² Research Center of Applied Electromagnetics, Nanjing University of Information Science and Technology, Nanjing 210044, China

³ State Key Laboratory of Millimeter Waves, Southeast University, Nanjing 210096, China

* Correspondence: hpwang@nuist.edu.cn

Abstract

Traditional design methods for ultra-wideband (UWB) filters rely on complex electromagnetic (EM) simulations and iterative parameter optimization, consuming significant computational resources and design time. Current inverse design approaches predominantly employ generative adversarial networks (GANs) and convolutional neural networks (CNNs). However, these models often produce blurry topological boundaries, rendering them inadequate for UWB filters that demand extremely precise modeling of intricate features, such as microscopic stubs and exceedingly narrow gaps. To overcome this bottleneck, this paper proposes an inverse design framework integrating a conditional diffusion model with an evolutionary algorithm. The conditional diffusion model is uniquely suited for UWB inverse design, directly incorporating target scattering parameters as explicit conditions during training strictly guides the generation trajectory. This mechanism enables the model to synthesize high-fidelity, fine-grained pixelated patterns that traditional networks fail to achieve. During the inverse design process, the conditional diffusion model generates candidate topology-guided target *S*-parameters. Subsequently, an evolutionary algorithm, coupled with a pre-trained ResNet fast evaluator, iteratively searches the latent space to pinpoint the optimal geometric structure matching the target EM response. Validation through multiple UWB filter examples demonstrates that simulated *S*-parameters exhibit excellent agreement with target curves, achieving an efficient and precise design from EM performance to geometric structure. The two final fabricated inverse-designed filters exhibit 3 dB passbands ranging from 5.67 to 12.40 GHz and 7.35 to 14.60 GHz, achieving high fractional bandwidths of 74.53% and 66.06%, respectively.

Keywords: ultra-wideband (UWB) filters; microstrip filters; conditional diffusion models; ResNet; inverse design



Academic Editor: Shahram Minaei

Received: 19 May 2026

Revised: 5 July 2026

Accepted: 7 July 2026

Published: 9 July 2026

Copyright: © 2026 by the authors.

Licensee MDPI, Basel, Switzerland.

This article is an open access article distributed under the terms and conditions of the [Creative Commons Attribution \(CC BY\)](https://creativecommons.org/licenses/by/4.0/) license.

1. Introduction

Microstrip filters, as the most widely utilized microwave components, have been developed into various configurations to meet diverse functional requirements [1,2]. Among these, ultra-wideband (UWB) filters serve as core elements for frequency selection in the front-end of UWB communication systems. Their performance directly dictates the anti-interference capability and transmission quality of the entire system [3,4]. Specifically, UWB filters are required not only to achieve extremely low insertion loss and stable

group delay characteristics across a broad spectrum but also to exhibit steep attenuation poles at passband edges. These features are essential to suppress potential interference from other wireless systems, such as wireless local area networks (WLAN) and radio frequency identification (RFID) [5–7]. However, due to the ultra-wide relative bandwidth and stringent in-band flatness requirements, the geometries of UWB filters often incorporate intricate elements such as multi-stage coupled lines, defected ground structures (DGS), or stepped-impedance resonators (SIR). These complex features result in a highly nonlinear mapping between design parameters and electromagnetic (EM) responses. Traditional design methodologies primarily rely on engineers extracting initial values from equivalent circuit models, followed by exhaustive and time-consuming parameter sweeps and optimization using full-wave EM simulation software. This process is heavily dependent on the empirical expertise of designers, and will frequently encounter the convergence to a global optimum when faced with multi-objective optimization challenges [8–11].

Benefiting from the rapid advancement of artificial intelligence, neural network-based design methods have significantly streamlined the development process. These methods are generally categorized into forward design and inverse design. Neural networks for inverse design offer a distinct efficiency advantage by directly generating geometric parameters that satisfy specific EM performance targets. Currently, inverse design architectures include convolutional neural networks (CNNs), variational autoencoders (VAEs), generative adversarial networks (GANs), and the recently prominent diffusion models. Each generative or discriminative model presents unique strengths and limitations. As a typical discriminative model, CNNs effectively map design parameters to EM responses but struggle with the “one-to-many” non-unique mapping problem in inverse design [12,13]. In contrast, VAEs introduce latent space distribution to generate diverse structures, thereby mitigating the non-uniqueness issue to some extent [14–16]. However, the reconstruction mechanism based on variational inference and the Evidence Lower Bound (ELBO) loss objective often results in an over-smoothing effect, causing inherent blurriness and noise in VAE-generated patterns. This lack of sharp edge definition restricts their application in designing intricate circuit structures such as UWB filters that demand precise modeling of narrow gaps. Compared with VAEs, GANs utilize an adversarial training mechanism between a generator and a discriminator, and can significantly improve image clarity and produce sharper patterns [17–19]. Nevertheless, GANs are intrinsically limited by their non-convergent minimax games, making them prone to mode collapse and training instability. In addition, the irreversibility of their generative process remains a challenge for comprehensive inverse mapping coverage. Diffusion models establish a novel probabilistic generative paradigm by defining a forward process of gradual noise injection and a parameterized reverse process of iterative denoising guided by score-matching [20–22]. These models can reconstruct high-fidelity circuit patterns from Gaussian noise through iterative denoising, achieving extreme precision in edge details. Therefore, diffusion models can be used to effectively overcome the blurring issues of VAEs and the adversarial instability of GANs, while allowing for conditional generation.

Recently, diffusion-based inverse design has achieved significant success in tasks involving complex electromagnetic (EM) structures such as metasurfaces and photonic crystals [23–27]. However, while an open-loop conditional diffusion model can achieve end-to-end generation from S-parameters to patterns, the quality of its output still requires EM simulation validation, lacking strict EM feedback constraints. To further enhance precision and fundamentally overcome this methodological limitation, a “generation-evaluation-optimization” closed-loop inverse design framework is proposed. This framework comprises two core networks: a conditional diffusion network for mapping target S-parameters to candidate pixelated patterns, and a ResNet prediction network acting as a fast EM

simulator for instantaneous evaluation. Furthermore, an evolutionary algorithm is introduced to perform an optimization search within the latent space of the diffusion model, iteratively identifying the optimal latent variables that best match the target S-parameters. This three-stage method utilizes the natural advantages of diffusion models in handling non-unique mappings while ensuring EM precision through the synergy of the prediction network and the evolutionary algorithm, providing a novel closed-loop solution for the intelligent design of UWB filters.

2. Inverse Design Methodology and Principles

2.1. Dataset Construction and Inverse Design Workflow

The samples in the training dataset consist of UWB microstrip filters composed of irregular rectangular patches. Several examples of the simulation models are illustrated in Figure 1a. These are primarily based on two resonator-type substrate configurations. For all resonators, two microstrip feed lines are connected to the left and right sides, with various symmetrical topologies situated in the center. Training the inverse design model requires two distinct datasets, designated as the geometric dataset and the S-parameter one. The construction process for these datasets is depicted in Figure 1a. Since the feed lines are fixed, only the central topological region of the patch is extracted to form the geometric dataset. Due to its inherent symmetry, only half of the topology is utilized for geometric characterization. It is represented as a pixelated binary image, where black pixels denote copper metallization and white pixels represent the unmetallized substrate. For the first configuration, the microstrip feed line length (L_{12}) and width (W_{12}) are 9 mm and 1.8 mm, respectively, with total filter dimensions (L_{11} and W_{11}) set to 19 mm and 12.8 mm. In the second configuration, the feed line length (L_{22}) and width (W_{22}) are 5.31 mm and 0.6 mm, with total dimensions (L_{21} and W_{21}) of 18.42 mm and 4.5 mm. Both types utilize a substrate thickness (h) of 0.508 mm, employing F4B material with a dielectric constant of 2.65.

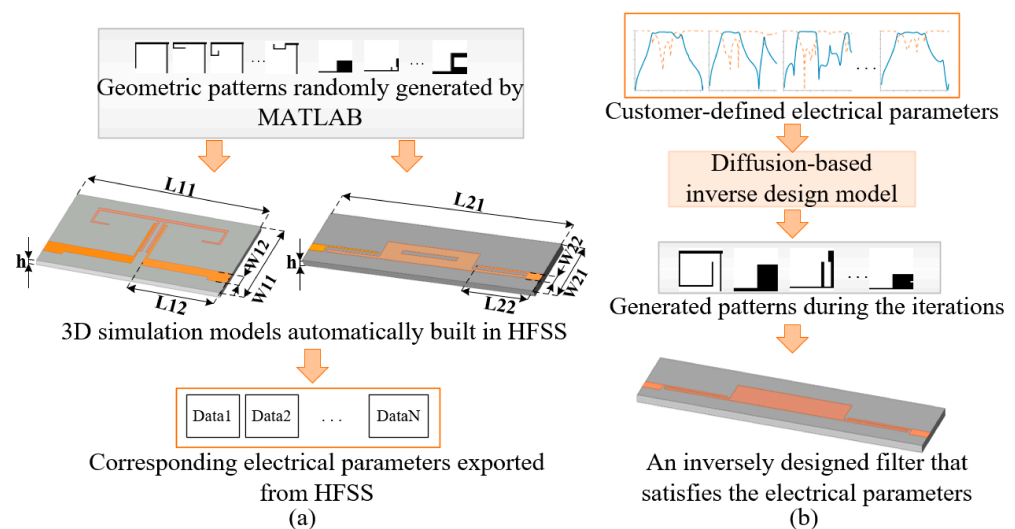


Figure 1. (a) Setup procedure of the geometric dataset and S-parameter dataset. (b) Overall design procedure of the ultra-wideband microstrip filters.

To enhance the diversity of the geometric dataset, seven common UWB topologies were selected, primarily including E-shaped stepped-impedance resonators (SIR), multi-mode resonators (MMR), and derivative structures with additional stubs. The training dataset contains 12,137 samples. By varying parameters such as the length and angle of specific branches or the dimensions of rectangular patches, a wide range of bandpass characteristics with different cutoff frequencies can be achieved. From an electromagnetic

standpoint, the generated pixelated topologies function as customized multi-mode resonators (MMRs). The binarized copper patches define highly convoluted surface current distribution paths, while the unmetallized pixel gaps act as slot lines regulating capacitive and inductive couplings. This localized resonant behavior concentrates currents at specific stopband edges to synthesize transmission zeros, thereby physically underlying the steep attenuation poles and sharp selectivity observed in the wideband responses without requiring traditional geometric regularity. Based on these topologies, filter models were automatically batch-constructed and simulated using MATLAB R2022b in conjunction with the finite-element EM software ANSYS HFSS 2019. The dataset generation and simulation configurations are strictly standardized. The geometric variations restrict the microstrip widths and gaps within a parameter range of 0.2 mm to 1.5 mm, which are explored using a uniform random sampling strategy via MATLAB. The compiled dataset comprises a total of 12,137 samples. Full-wave simulations were performed using the ANSYS HFSS frequency-domain finite element method (FEM) solver with an interpolating sweep from 0 to 26 GHz. The adaptive mesh refinement is governed by a maximum Delta S of 0.02 with a limit of 20 adaptive passes. With an average simulation time of 1.5 min per device, the comprehensive dataset was successfully compiled offline within approximately 30 h. These simulations yielded scattering parameters, specifically the transmission coefficient (S_{21}) and the reflection coefficient (S_{11}). Ultimately, the pixelated patterns and their corresponding simulation results were processed into the two training datasets. The comprehensive design workflow for the UWB filter is illustrated in Figure 1b. To design a filter with specific center frequency and bandwidth requirements, the desired S-parameter curves (comprising 512 data points for both S_{11} and S_{21}) are selected as conditional inputs for the trained model. These S-parameters are represented in a normalized format, exhibiting ideal passband characteristics with zero insertion loss and infinite return loss. Although these target masks are geometrically ideal, they are almost identical to actual physical effects during the genetic algorithm optimization stage because the ResNet evaluator is trained entirely on HFSS data, which itself contains finite substrate loss and conductor roughness. Upon inputting the customized EM parameters into the diffusion-based inverse design model, the model initiates from constructed random noise. Under the continuous guidance of the target S-parameters, the model reconstructs a unique pixelated pattern satisfying the performance requirements through an iterative denoising process. Finally, the generated optimal pattern is used to construct a 3D simulation model for physical validation. The detailed information of the geometric training datasets is presented in Supplementary Section S1.

2.2. Conditional Diffusion Model Principles and Architecture

The proposed framework utilizes a conditional diffusion model to learn the complex distribution of UWB microstrip filters, offering distinct theoretical advantages over traditional generative architectures like VAEs and GANs. Owing to the evidence lower bound (ELBO) objective, VAEs often produce blurred geometric contours by assigning excessive probability mass to the distribution mean, which smooths over the high-frequency edge details essential for EM performance. Despite the capacity for generating sharp visual outputs, GANs often exhibit training instability and mode collapse due to the adversarial failure to reach a stable Nash equilibrium. Consequently, this limitation hinders their ability to faithfully represent the full diversity of the target distribution. In contrast, the diffusion model defines a generative process via a reversible sequence of Gaussian transitions, utilizing score-matching to learn the gradient of the log-density across the manifold. By decomposing generation into a multi-step iterative denoising pipeline, it avoids the representational bottlenecks of VAEs and the instability of GANs.

As illustrated in the training phase of Figure 2, Gaussian noise is incrementally added to the initial pattern x_0 until it transforms into isotropic noise x_T . The noisy representation at any step t is expressed as $x_t = \sqrt{\bar{\alpha}_t}x_0 + \sqrt{1 - \bar{\alpha}_t}\epsilon$, where $\epsilon \sim N(0, I)$. A neural network ϵ_θ is trained to predict the added noise ϵ by minimizing the Mean Squared Error (MSE): $L = E_{x_0, \epsilon, t, z} [\|\epsilon - \epsilon_\theta(x_t, t, z)\|^2]$, where z denotes the conditional S -parameters. The forward and backward processes operate under a linear noise scheduler spanning $T = 1000$ sequential timesteps, with the noise variance boundaries set from $\beta_{\text{start}} = 10^{-4}$ to $\beta_{\text{end}} = 0.02$. The target S -parameter condition vector y is mapped through a dedicated fully connected embedding network and injected into the intermediate channels of the U-Net via cross-attention mechanisms at each downsampling and upsampling stage. The objective loss function utilizes a uniform loss weighting scheme across all timesteps without classifier-free guidance. Mathematically, the network is optimized by minimizing the conditional mean squared error:

$$\mathcal{L} = \mathbb{E}_{t, x_0, \epsilon} [\|\epsilon - \epsilon_\theta(x_t, t, y)\|^2] \quad (1)$$

where x_t represents the corrupted microstrip layout at timestep t . The network parameters were optimized using the Adam optimizer with a learning rate of 2×10^{-4} for a total of 400,000 training iterations. During the Sampling Phase, the model reconstructs the geometry from random noise through T iterative denoising steps. The core backbone, detailed in Figure 3, adopts a symmetric U-Net architecture. The Encoder progressively downsamples the $32 \times 32 \times 1$ input into a compact $8 \times 8 \times 256$ latent representation using Conv2D layers (stride = 2), integrated with Group Normalization and Sigmoid Linear Unit (SiLU) activations. Conversely, the Decoder recovers high-fidelity features through ConvTranspose2D layers and residual blocks. This bottleneck design, supplemented by skip connections, ensures the precise reconstruction of intricate microstrip contours guided by specific EM requirements.

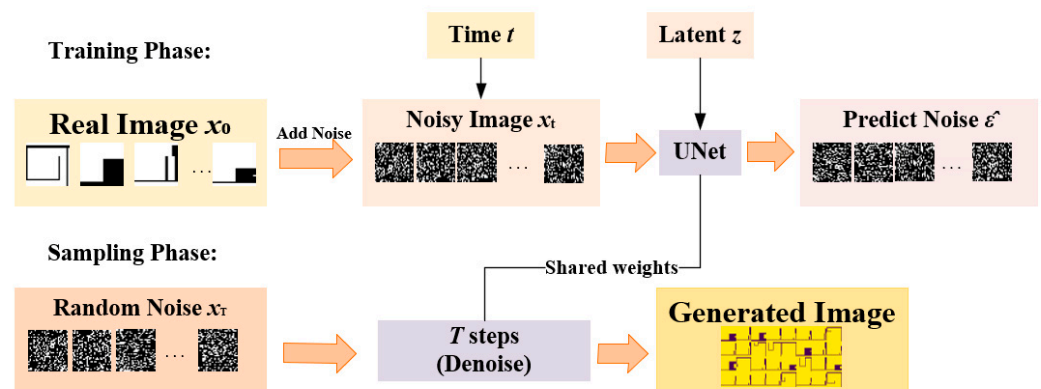


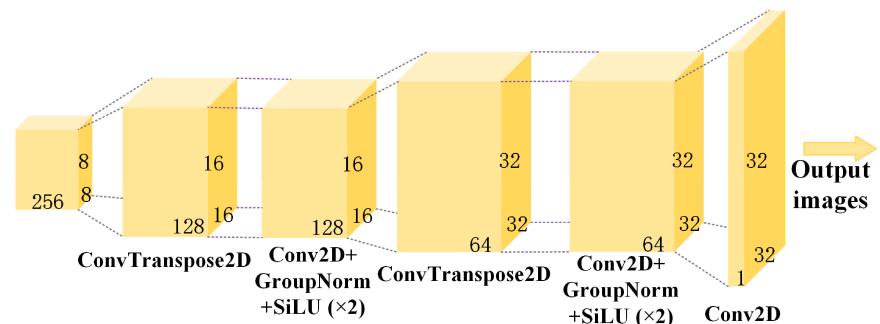
Figure 2. Operational pipeline of the proposed conditional diffusion model across forward noise injection and iterative reverse denoising phases.

2.3. Working Principle and Performance of the Prediction Network

To achieve rapid evaluation of the EM performance of patterns generated by the conditional diffusion model, a S -parameter prediction model based on the deep residual network (ResNet) is constructed. Serving as a high-speed EM simulator within the inverse design closed loop, this model maps 32×32 pixelated patterns to corresponding S -parameter curves accurately and efficiently, providing instantaneous feedback for latent variable optimization. The core of the predictor utilizes a residual structure designed to learn identity mappings via skip connections, effectively mitigating the vanishing gradient

problem in deep architectures and enabling the network to capture the highly nonlinear relationship between geometry and EM response.

Encoder:



Decoder:

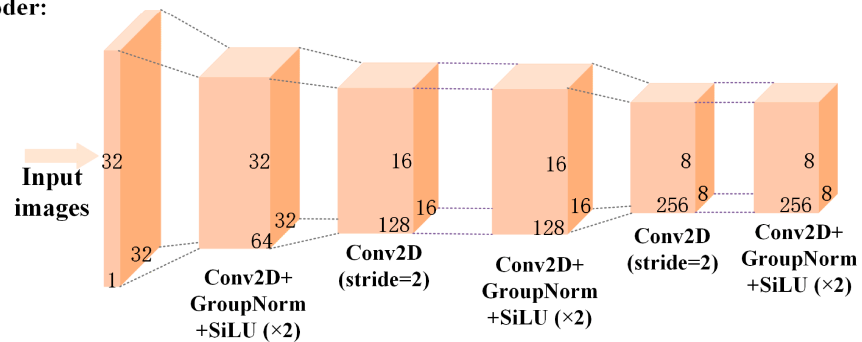


Figure 3. Structural layout of the symmetric U-Net backbone architecture with group normalization and residual recovery pathways.

The input layer receives a $32 \times 32 \times 1$ binarized filter pattern. The backbone consists of multiple stacked residual blocks, each containing two sequences of “Convolution-BatchNormalization-ReLU” operations, with feature reuse facilitated by identity mapping. The fundamental design of the residual block is formalized as

$$y = F(x, \{W_i\}) + x \quad (2)$$

where F represents the residual mapping to be learned, comprising two convolutional layers and their associated normalization and activation functions. This architecture ensures that gradients flow directly through skip connections during backpropagation, bypassing potential vanishing issues.

The specific architecture is depicted in Figure 4. The input image first passes through an initial convolutional layer to expand the channel dimension to 32, followed by four stages of residual processing. Each stage contains two residual blocks, with spatial downsampling achieved via a stride of 2 in the first block of each stage. Through this progressive downsampling, the spatial resolution is reduced from 32×32 to 16×16 , 8×8 , and finally 4×4 , while the channel count expands from 32 to 64, 128, and 256. This “spatial compression and channel expansion” paradigm allows the network to extract multi-scale features ranging from local details (edges and corners) to global topologies (resonator layouts and coupling paths). After feature extraction, a global average pooling (GAP) layer compresses the $4 \times 4 \times 256$ feature map into a 256-dimensional vector, mitigating the parameter overhead associated with fully connected layers. This is followed by two fully connected layers for nonlinear transformation, each integrated with dropout (0.3) to prevent overfitting. The final output layer is a 512-dimensional linear layer, corresponding to 256 sampling points each for S_{11} and S_{21} within the 0–26 GHz range.

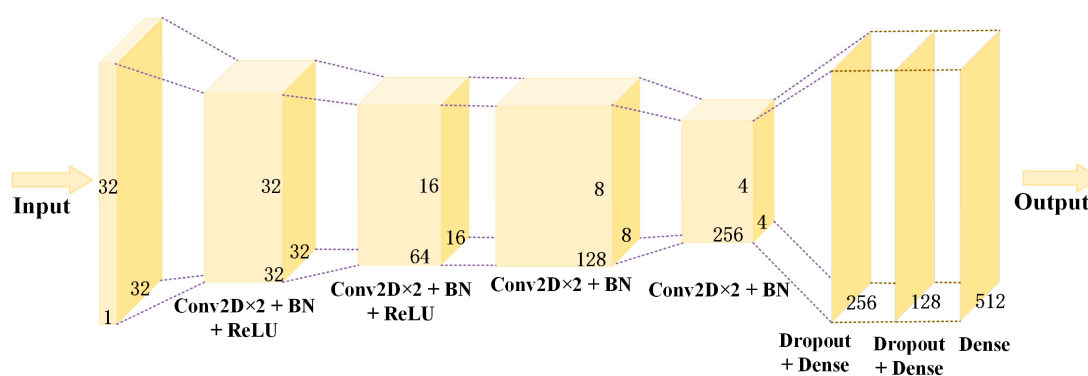


Figure 4. Architectural schematic of the ResNet-based electromagnetic surrogate predictor showing multidimensional feature mapping.

MSE and Mean Absolute Error (MAE_{resnet}) are introduced to evaluate the simulator's performance, defined as

$$MSE_{resnet} = \frac{1}{n} \sum_{i=1}^n |R_{it} - R_{ip}|^2 \quad (3)$$

$$MAE = \frac{1}{n} \sum_{i=1}^n |R_{it} - R_{ip}| \quad (4)$$

where n is the total number of samples evaluated, R_{it} denotes the true target response for the i th sample, and R_{ip} represents the corresponding predicted response generated by the simulator.

The dataset is partitioned into training, validation, and test sets with a ratio of 60:20:20, ensuring non-overlapping distributions. The network is trained using the Adam optimizer with an initial learning rate of 5×10^{-5} and a gradient clipping threshold of 1.0 to prevent exploding gradients. Training proceeds for 10,000 iterations with a batch size of 64. As shown in Figure 5, both MSE and MAE_{resnet} converge steadily, with the final validation MSE and MAE_{resnet} reaching 1.99×10^{-3} and 1.864×10^{-2} , respectively. The close alignment between training and validation curves indicates a robust model without significant overfitting.

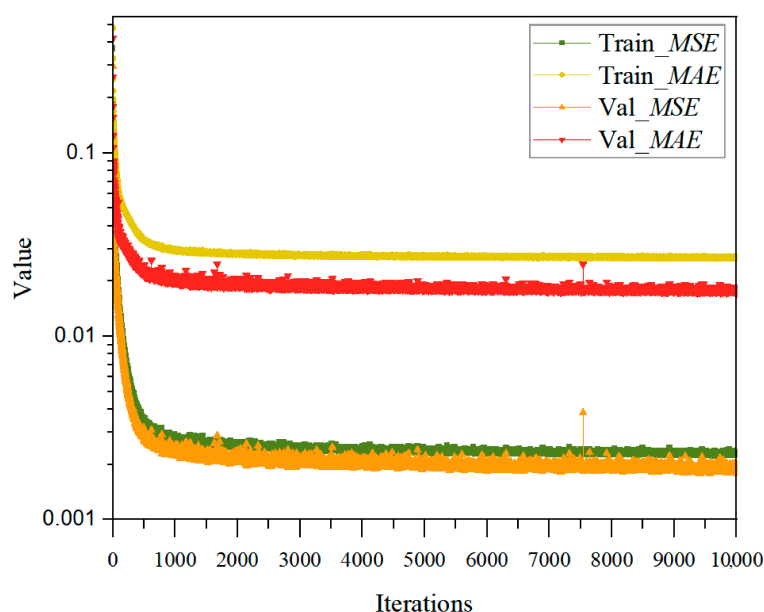


Figure 5. MAE and MSE of the training and validation sets during ResNet iterative training.

To rigorously evaluate the reliability and robustness of the ResNet-based predictor, a comprehensive statistical analysis was conducted on the independent test suite ($N = 2428$). The quantitative evaluation metrics across the full frequency band (0–26 GHz) are summarized in Table 1. Specifically, the MAE_{resnet} between the surrogate predictions and electromagnetic simulations was 0.0181 ± 0.0207 dB (mean $\pm$ SD), indicating minimal prediction uncertainty. The 95% confidence interval of the prediction error was tightly bounded within [0.0173, 0.0189] dB. Furthermore, an evaluation of the worst-case scenario revealed that the maximum prediction error among all test samples was only 0.2594 dB, which is well within acceptable fabrication and engineering tolerances. Additionally, a paired t -test was performed between the predicted values and the HFSS ground truth to verify that the surrogate model introduces no systematic bias. The extremely small mean difference was 0.000078 dB, and the resulting p -value was 0.189 ($t = 1.314$, $p > 0.05$), demonstrating that no statistically significant difference exists between the ResNet predictions and the rigorous electromagnetic simulations. Consequently, the high fidelity of the surrogate predictor guarantees the overall performance and practical applicability of the proposed closed-loop inverse design framework.

Table 1. Quantitative evaluation of the surrogate predictor performance.

	Mean (dB)	Std. Deviation (dB)	Std. Error Mean (dB)	95% Confidence Interval (dB)		t	df	p-Value	Worst-Case Prediction Errors (dB)	Uncertainty Analysis (dB)
				Upper Limit	Lower Limit					
test-predict	0.000078	0.002942	0.000060	−0.000039	0.000196	1.3140	2427	1.88962×10^{-1}	0.25944	0.02067

2.4. Latent Space Optimization via GA

To bridge the gap between generative diversity and electromagnetic precision, a Genetic Algorithm (GA) is employed to optimize the latent variable space of the diffusion model. The optimization objective is formulated to minimize the discrepancy between the target S -parameters and those of the generated structures. This discrepancy is quantified by the $L2$ norm (Euclidean distance), defined as follows:

$$L2 = - \| T_{goal} - T_{generated} \|_2 = - \sqrt{\frac{\sum_{i=1}^n \left(T_{goal}(f_i) - T_{generated}(f_i) \right)^2}{n}} \quad (5)$$

where n is the number of frequency sampling points, while T_{goal} and $T_{generated}$ represent the target values and the predicted responses, respectively.

The overall optimization framework, illustrated in Figure 6, integrates the generative diffusion model, the ResNet-based surrogate model, and the genetic algorithm (GA) into a closed loop. Initially, a population is stochastically initialized, where each individual is represented by a 128-dimensional latent vector z . These vectors serve as the input for the trained diffusion model to generate candidate pixelated patterns. Subsequently, the ResNet-based EM predictor rapidly calculates the corresponding S -parameters (S_{11} and S_{21}) for each pattern. The fitness of each individual is evaluated based on the MSE relative to the target curves, with higher fitness scores assigned to individuals whose EM performance most closely aligns with the design specifications. Following the fitness evaluation and ranking, the population enters the evolutionary phase. High-fitness individuals are selected as parents to produce offspring through crossover, which enables information recombination by swapping gene segments (latent vector components) between parent pairs. To maintain population diversity and avoid local optima, stochastic mutation is performed by injecting Gaussian noise into random dimensions of the latent vectors. To prevent the loss of the

best solutions, the individual with the highest fitness score is directly copied to the next generation without undergoing crossover or mutation. This iterative cycle of generation, prediction, and evaluation continues until the convergence criteria are met. Specifically, the GA utilizes a population size of $N = 50$, a crossover probability of $P_c = 0.8$, and a Gaussian mutation rate of $P_m = 0.05$. The termination criterion is enforced when the elite fitness improvement falls below 10^{-5} for 15 consecutive generations, or the maximum generation reaches $G = 100$. Regarding the computational complexity and operational environment, the entire framework was developed within the PyCharm IDE 2019.2.6 using TensorFlow-GPU 1.14, running on an Ubuntu 16.04 OS equipped with an NVIDIA GPU server environment (NVIDIA driver 418.56, CUDA 10.0, and cuDNN 7.5). The offline training required approximately 7.8 h for the diffusion network. During the online synthesis phase, the reported average inverse design latency of 20.128 min per sample is primarily attributed to the long-sequence sequential dependency of the diffusion network, which requires $T = 1000$ iterative denoising timesteps compounded across the evolutionary population space. Although this runtime is higher than single-step alternatives, this step-by-step sampling trajectory acts as a rigorous mathematical regularizer that yields high structural fidelity and topological precision for UWB microstrip patterns. When compared with traditional empirical optimization-based EM synthesis methods, the proposed closed-loop synthesis offers a highly robust, high-accuracy, and automated engineering paradigm. Finally, the optimal latent vector is exported to generate the high-performance UWB filter geometry for physical validation.

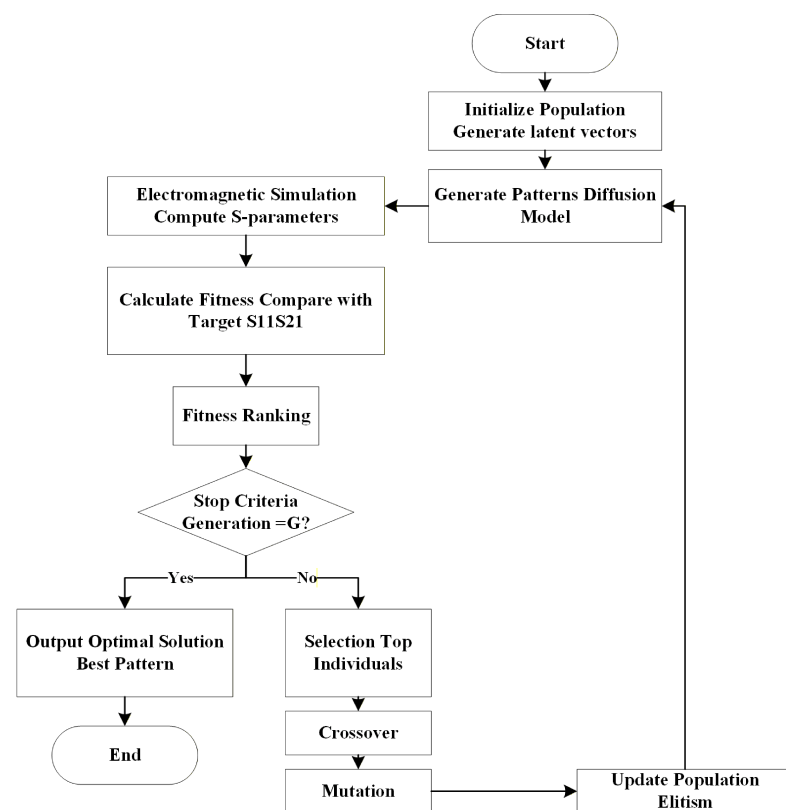


Figure 6. The flowchart of the genetic algorithm (GA) optimizer used in the inverse design of microstrip filters.

Our hybrid framework functions as a unified sequence: the diffusion network performs structural synthesis within a continuous latent space; the surrogate model provides the necessary gradient mapping to bridge generative synthesis and electromagnetic simulation; and the optimization loop acts as an essential error-correction mechanism for the

synthesized results. We emphasize that these components are architecturally interdependent and collectively essential for achieving the reported performance.

To quantitatively evaluate the statistical robustness of the generative algorithms across stochastic initializations, $N = 10$ independent inverse design runs were executed for a fixed target response. The statistical metrics, including the mean, standard deviation (SD), and 95% confidence intervals (CI) of the $MAE_{inverse}$, were rigorously calculated, as shown in Table 2. The proposed Diffusion model achieved the lowest Mean $MAE_{inverse}$ of 0.0137 with an exceptionally small SD of 3×10^{-5} (95% CI : [0.0137, 0.0137]), demonstrating outstanding algorithmic stability. In contrast, the other methods exhibited significantly higher variance. The $MAE_{inverse}$ is defined as follows:

$$MAE_{inverse} = \frac{1}{n} \sum_{i=1}^n |S_{target}(f_i) - S_{actual}(f_i)| \quad (6)$$

where n is the number of frequency sampling points, while $S_{target}(f_i)$ and $S_{actual}(f_i)$ represent the desired specifications and the full-wave simulated responses at the i -th frequency point, respectively.

Table 2. Non-parametric Kruskal–Wallis test for various inverse design methods.

Model	Traditional_GA	VAE	GAN	Transformer	Diffusion
Mean (dB)	0.8197	0.0628	0.0623	0.0886	0.0137
Standard deviation (dB)	0.002511	0.006414	0.007413	0.068002	0.000028
95% Confidence Interval (dB)	[0.8179, 0.8215]	[0.0582, 0.0674]	[0.0570, 0.0676]	[0.0400, 0.1373]	[0.0137, 0.0137]

It should be noted that the 95% confidence intervals for the median across the 10 independent trials were calculated using a non-parametric method based on order statistics, which inherently aligns with the applied Kruskal–Wallis test. Assuming the independent sample observations of size n are arranged in ascending order, denoted as $X_{(1)} \leq X_{(2)} \leq \dots \leq X_{(n)}$, the confidence interval is defined by the bounds $[X_{(j)}, X_{(k)}]$. The exact confidence level $1 - \alpha$ for this interval is determined by the cumulative binomial distribution function:

$$1 - \alpha = \sum_{i=j}^{k-1} \binom{n}{i} (0.5)^n \quad (7)$$

where $n = 10$, and the ranks j and k are selected symmetrically to satisfy a confidence level of at least 95% ($\alpha \leq 0.05$). The fundamental assumption of this non-parametric calculation is strictly that the samples are independent and identically distributed, bypassing the requirement for the underlying data to be normally distributed. The exceptionally narrow width of the resulting confidence interval for the diffusion model is a direct mathematical consequence of the highly clustered evaluation metrics achieved across these specific trials, resulting in adjacent order statistics with minimal variance.

The statistical robustness and error distributions across 10 independent runs for all five inverse design architectures are visually compared via the boxplot in Figure 7. The $MAE_{inverse}$ value across the 10 evaluation trials was 0.8192 ± 0.0036 (median $\pm$ interquartile range) for the Traditional_GA, 0.0645 ± 0.0091 for the VAE, 0.0630 ± 0.0044 for the GAN, 0.0652 ± 0.0277 for the Transformer, and 0.0137 ± 0.0001 for the proposed Diffusion model. The non-parametric Kruskal–Wallis test results indicate that the proposed Diffusion model achieves the lowest and most stable error distribution among all methods ($H = 38.10$, $p < 0.0001$). Specifically, pairwise comparisons demonstrate that the Diffusion model exhibits significantly lower $MAE_{inverse}$ values than the Traditional_GA protocol

($p < 0.001$), the VAE network ($p < 0.05$), and the modern Transformer architecture ($p < 0.01$). Although the Transformer network demonstrated the capacity to capture overall structural topologies, outperforming the Traditional_GA in terms of the median index, it exhibited a much wider error fluctuation (ranging up to 0.2730) and a significantly higher median error than the Diffusion model. This limitation is primarily associated with traditional transformer architectures, which emphasize global context but may lack local inductive bias. Modern vision transformer models contain hierarchical or hybrid mechanisms for better local feature extraction to mitigate these limitations. However, within the specific baseline configurations evaluated in this study, the diffusion network presented a more stable optimal trade-off between structural stability and prediction precision for microstrip gaps. Detailed data of the Kruskal–Wallis test results are provided in Supplementary Section S2.

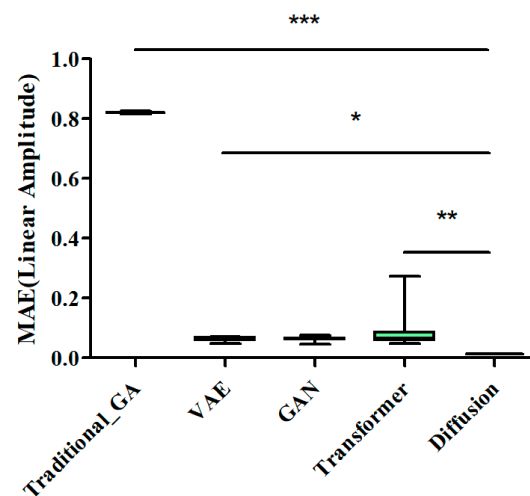


Figure 7. Statistical distribution of the $MAE_{inverse}$ across 10 independent runs for various inverse design methods. The Kruskal–Wallis test was employed to evaluate statistical changes, and significance markers indicate statistically significant differences compared with the proposed Diffusion model (* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$).

3. Results and Discussions

3.1. Performance Comparison of Inverse Design Networks

Table 3 quantitatively benchmarks the proposed conditional diffusion model against GAN and VAE architectures using model-independent standardized metrics on the test set. The most striking observation is the magnitude of difference in structural and electromagnetic fidelity. The proposed conditional diffusion model achieves an exceptional Fréchet inception distance (FID) of 12.45 and a structural similarity index measure (SSIM) of 0.941, representing unparalleled boundary sharpness and layout continuity. This structural precision directly translates into the electromagnetic domain, where our model delivers a highly suppressed S-parameter error (EM MSE_S , quantifying the discrepancy between the synthesized and target scattering coefficients), which is two to three orders of magnitude lower than the baseline networks. This disparity reflects the fundamental difference in their learning paradigms. In GANs, the adversarial equilibrium exhibits generalized structural tracking but suffers from edge noise (SSIM = 0.724); however, the relatively high loss and stability ($\sigma = 0.496$) underscore the inherent difficulty of reaching a fine-grained global minimum in a non-convergent minimax game. For VAEs, the high loss and extreme instability ($\sigma = 61.21$) stem from the intrinsic tension between reconstruction accuracy and latent space regularization, often resulting in “posterior collapse” or blurred outputs in intricate UWB topologies. Conversely, the conditional diffusion model demonstrates high optimization robustness. Its stability ($\sigma = 2.1 \times 10^{-4}$) indicates a highly smooth and

well-behaved loss surface. By employing a score-matching objective, the diffusion model effectively learns the exact gradient field of the data distribution, allowing for the reconstruction of high-frequency geometric features that are typically lost in VAEs or distorted in GANs. Regarding computational efficiency, although the diffusion model exhibits a higher inverse design latency (20.128 min/sample) due to the T-step iterative denoising process, it offers a more favorable training profile. It converges in 7.8 h—nearly 40% faster than GAN—suggesting that the diffusion framework avoids the training stagnation common in adversarial training. This trade-off between inference time and structural fidelity is highly advantageous for UWB filter design, where EM precision is paramount. The comprehensive specifications regarding the network architectures, core hyperparameters, and standardized training conditions applied to guarantee a fair and reproducible performance comparison among the three networks are detailed in Supplementary Section S3.

Table 3. Quantitative comparison of training stability and efficiency across generative models.

Model	FID	SSIM	Training Time (401k Iters) (h)	Inverse Design Time (min)	EM MSE _S	Stability (σ)
GAN	34.12	0.724	13.4	10.436	2.23×10^{-2}	0.496
VAE	58.67	0.615	4.5	15.275	6.20×10^{-1}	61.21
Conditional Diffusion	12.45	0.941	7.8	20.128	4.20×10^{-4}	0.00021

To further validate the inverse design efficacy, Figure 8 presents a comparative analysis of the reconstructed geometries and their corresponding spectral responses for identical database targets. The conditional diffusion model exhibits high topological fidelity; unlike the GAN and VAE results, which frequently suffer from blurred contours or structural artifacts, the diffusion-generated patterns maintain sharp, well-defined boundaries that accurately represent the intricate coupling structures essential for UWB performance. This structural integrity is directly reflected in the spectral domain, where the predicted S_{11} and S_{21} curves for the diffusion-generated samples achieve close agreement with the database target curves across the entire 0–26 GHz bandwidth. In contrast, the GAN and VAE results exhibit noticeable deviations, particularly in the passband ripple and out-of-band rejection levels, indicating their limitations in resolving the sensitive multi-objective trade-offs inherent in microstrip filter design. To rigorously validate the robustness and stability of the proposed framework across multiple independent runs, an extensive set of additional diverse inverse design test cases for the three networks is presented in Supplementary Section S4.

The quantitative data provided in Table 4 reinforces these qualitative observations. The conditional diffusion model achieves a curve similarity of 99.81%, effectively bridging the gap between design intent and physical realization. Notably, the proposed conditional diffusion model framework not only satisfies the target specifications but occasionally optimizes them, as demonstrated by the in-band flatness and out-of-band rejection metrics, which exhibit the closest proximity to the required targets. These results demonstrate that the integrated “generation-evaluation-optimization” paradigm effectively handles the non-unique one-to-many mapping problem. By leveraging the score-matching objective of diffusion models alongside the precise search capability of the evolutionary algorithm in the latent space, the framework ensures a robust convergence toward a globally optimal solution. An internal ablation analysis highlights that the individual components are indispensable: the diffusion network restricts candidates within a realistic topological space, the ResNet surrogate bypasses exhaustive simulation time, and the GA eliminates open-loop generation noise to achieve the 99.81% precision benchmark. This integrated

synergy provides a highly accurate and intelligent solution for advanced microwave component design.

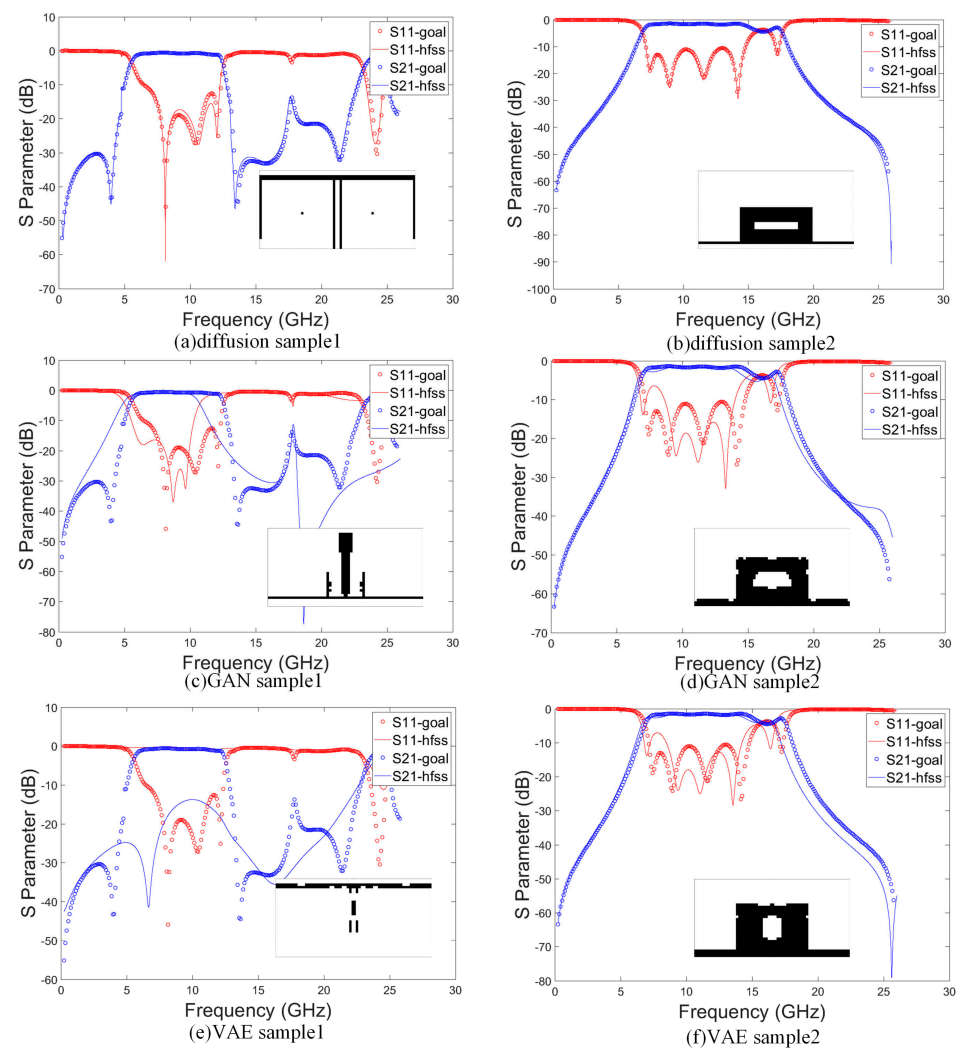


Figure 8. Generated patterns and simulated results (S_{11} and S_{21}) of the single-band filters with different customized center frequency (f_c) of (a,b) 4.6 GHz, (c,d) 5GHz, and (e,f) 5.4GHz.

Table 4. Quantitative comparison of inverse design performance.

Nets.	Absolute Bandwidth (GHz)	Relative Bandwidth (GHz)	In-Band Flatness (dB)	Out-of-Band Rejection (dB)	Curve Similarity (%)
Target Specification	10.67	87.31	3.11	33.22	\
GAN	10.32	87.43	3.7	29.87	95.85
VAE	10.89	86.66	3.0	33.23	95.12
Cond. Diffusion	10.69	87.54	2.99	33.32	99.81

The target specification in Table 4 refers to the same representative sample illustrated in Figure 8b,d,f.

The metric ‘Curve Similarity (%)’ reported in Table 2 is formally quantified using the normalized cross-correlation coefficient between the target spectral curves and the full-wave simulated curves, defined as follows:

$$CS = \frac{1}{2} \left[\frac{\sum_{i=1}^N S_{11}^{target}(f_i) \cdot S_{11}^{sim}(f_i)}{\sqrt{\sum_{i=1}^N [S_{11}^{target}(f_i)]^2 \cdot \sum_{i=1}^N [S_{11}^{sim}(f_i)]^2}} + \frac{\sum_{i=1}^N S_{21}^{target}(f_i) \cdot S_{21}^{sim}(f_i)}{\sqrt{\sum_{i=1}^N [S_{21}^{target}(f_i)]^2 \cdot \sum_{i=1}^N [S_{21}^{sim}(f_i)]^2}} \right] \times 100\% \quad (8)$$

where $N = 512$ represents the total number of frequency sampling points across the 0–26 GHz range.

3.2. Verification of the Custom Curve Inverse Design Model Based on Conditional Diffusion Model

Building upon the validation of the inverse design framework using database-derived targets, this section explores the synthesis of UWB filters tailored to customized spectral requirements. For arbitrary target curves, the total frequency spectrum (0–26GHz) is partitioned into several sub-bands, where independent thresholds for S_{11} and S_{21} are prescribed to formulate a piecewise objective function. As expressed in (8)–(10):

$$L = \gamma \times LS_{11} + (1 - \gamma) \times LS_{21} \quad (9)$$

$$LS_{11} = (S_{11} - S_{11min})(S_{11} - S_{11max})^T + \left| (S_{11} - S_{11min})(S_{11} - S_{11max})^T \right| \quad (10)$$

$$LS_{21} = (S_{21} - S_{21min})(S_{21} - S_{21min})^T + \left| (S_{21} - S_{21min})(S_{21} - S_{21max})^T \right| \quad (11)$$

the total loss L comprises the weighted sum of reflection loss (LS_{11}) and transmission loss (LS_{21}), modulated by a weighting coefficient γ . This penalty-based formulation utilizes row vectors S_{min} and S_{max} to define the desired spectral mask, where the squared difference between the EM responses and their respective boundaries determines the structural refinement direction.

The integrated design pipeline leverages the trained Conditional Diffusion model as the generator and the ResNet as the high-speed evaluator. Specifically, the 0–26 GHz range is divided into five discrete sub-bands. Within each band, normalized threshold masks are established to quantify the discrepancy between the predicted S -parameters and the customized objectives. By aggregating the sub-band losses into a global evaluation metric, the framework iteratively explores the latent space to identify the optimal pixelated geometry that satisfies the prescribed multi-band constraints.

To demonstrate the flexibility of the proposed approach, four distinct UWB filter designs with varying center frequencies (f_c) and 3 dB bandwidths (BW) were synthesized. As depicted in Figure 9, these designs targeted f_c at 10.5, 8.5, 9, and 11.5 GHz, respectively, all with a prescribed bandwidth of 7 GHz. The corresponding full-wave simulation results yielded actual center frequencies of 10.56, 8.475, 8.97, and 11.45 GHz, with 3 dB bandwidths measured at 7.73, 6.59, 6.78, and 6.82 GHz. The small deviation between the design specifications and simulation performance (center frequency error less than 1%) confirms that the model can accurately reconstruct complex microstrip topologies for non-database targets. The successful synthesis of this customized curve demonstrates the framework’s strong out-of-distribution (OOD) generalization ability. Since the score-matching target of the conditional diffusion network learns the underlying gradient field of the design space rather than memorizing a fixed template, it can effectively extrapolate and interpolate the effective topological boundaries of completely unknown frequency responses when combined with latent space search using a genetic algorithm, thus verifying its practical

application value in general filter synthesis. These results confirm that the “generation-evaluation-optimization” paradigm facilitates an efficient, high-precision transition from arbitrary EM requirements to physical geometric realization. The detailed information of the detailed approach to the inverse design of custom filters is presented in Supplementary Section S5.

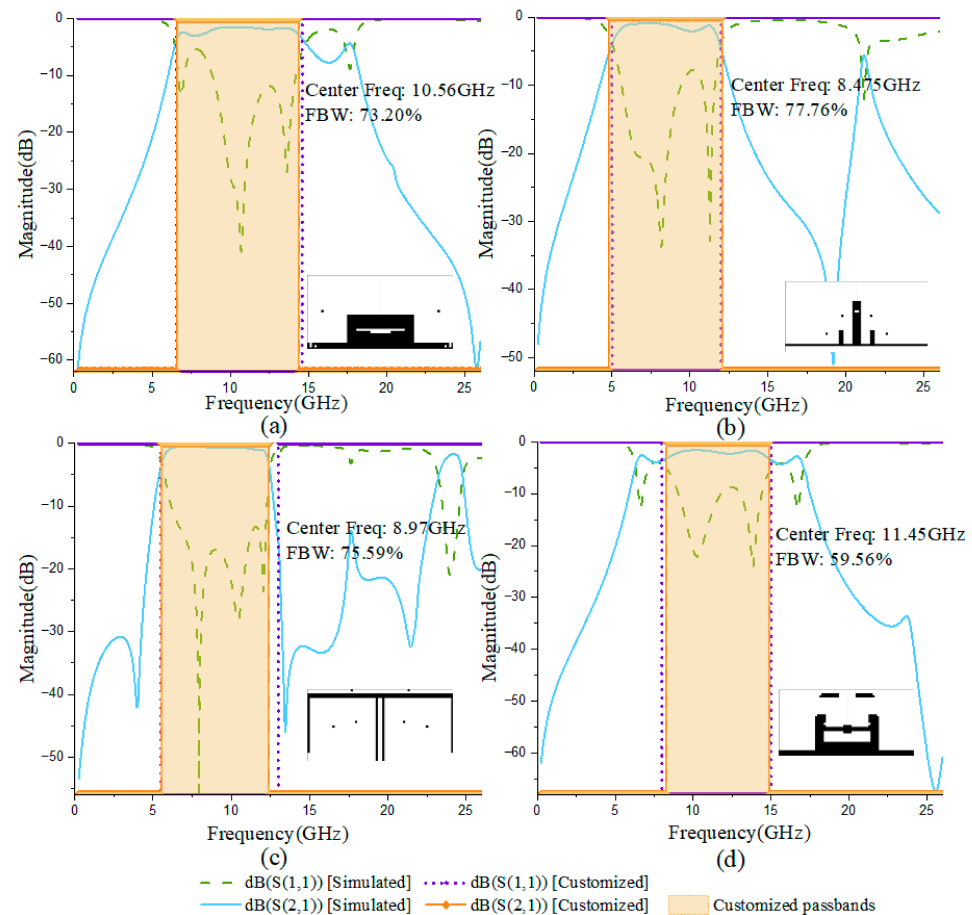


Figure 9. Examples of Custom Target Curve Design. (a) The center frequency is set to 10.5 GHz, and the 3dB bandwidth is 7–14 GHz; (b) The center frequency is set to 8.5 GHz, and the 3dB bandwidth is 5–12 GHz; (c) The center frequency is set to 9 GHz, and the 3dB bandwidth is 6–13 GHz; (d) The center frequency is set to 11.5 GHz, and the 3dB bandwidth is 8–15 GHz.

3.3. Experimental Validation and Measurement

To validate the practical efficacy of the proposed inverse design framework, a representative filter prototype with an overall footprint of 18.42×4.5 mm was fabricated. The prototype was realized on a 0.5 mm thick F4B substrate, featuring a 1-oz (35 μm) copper cladding on both the top and bottom layers to ensure low ohmic loss. High-frequency precision was maintained by soldering specialized D550M0202F05 RF connectors (manufactured by ALLWIN, Nanjing, China) to the feed lines. These connectors are specifically designed for millimeter-wave applications, ensuring stable transitions and minimal parasitic interference during high-frequency operation.

The scattering parameters were characterized using an Agilent Technologies N5227A PNA Network Analyzer (Serial No. US51270368, Agilent, Nanjing, China) over a wide frequency sweep from 100 MHz to 26 GHz. After standard SOLT (Short-Open-Load-Thru) calibration, the measured S_{11} and S_{21} responses were recorded and compared with the simulated data. As shown in Figure 10, to convincingly demonstrate the robustness and practical generalizability of the proposed framework, two automatically generated struc-

tures targeting different specifications were fabricated and measured. The measured curves for both prototypes exhibit a high degree of correlation with the HFSS simulation results across the entire ultra-wideband range. For the first specification (Figure 9a), the filter exhibits a peak transmission coefficient (S_{21}) of -1.50 dB at 7.87 GHz, indicating low insertion loss across the primary passband. The measured 3 dB absolute bandwidth is 6.734 GHz, spanning from 5.67 GHz to 12.40 GHz. This corresponds to a center frequency of 9.0355 GHz and a high fractional bandwidth of 74.53%, confirming its ultra-wideband characteristics. Within the operating band, the flatness is maintained at 2.64 dB. Beyond magnitude characteristics, the in-band group delay and phase linearity were carefully evaluated to verify signal stability across the wide spectrum. The extracted results demonstrate that the group delay remains remarkably flat within the core 5.67 to 12.40 GHz passband, maintaining a minor fluctuation below 0.35 ns, while the transmission phase response displays distinct linearity. This stable in-band phase variation confirms that the automatically generated irregular patch layout preserves high signal integrity and successfully suppresses phase distortion for ultra-wideband operations. Furthermore, the filter demonstrates exceptional selectivity at the lower frequency end, with an out-of-band rejection of 56.50 dB at 100 MHz relative to the peak. At the high-frequency stopband (near 26 GHz), the rejection level is recorded at 14.53 dB. Similarly, the second fabricated filter further confirms the framework's practical adaptability. For this design, the measured peak transmission coefficient (S_{21}) is 0.13 dB, indicating excellent in-band transmission efficiency. The filter covers a 3 dB passband from 7.35 GHz to 14.60 GHz, corresponding to a center frequency of 10.98 GHz. Furthermore, the prototype achieves a strict out-of-band rejection of 57.38 dB at the lower frequency end (0.10 GHz) and maintains strong suppression at the high-frequency stopband. The measured S -parameters highly coincide with the HFSS full-wave simulations, which demonstrates that the generative diffusion algorithm can robustly generalize to varying target bands while ensuring precise physical realizability.

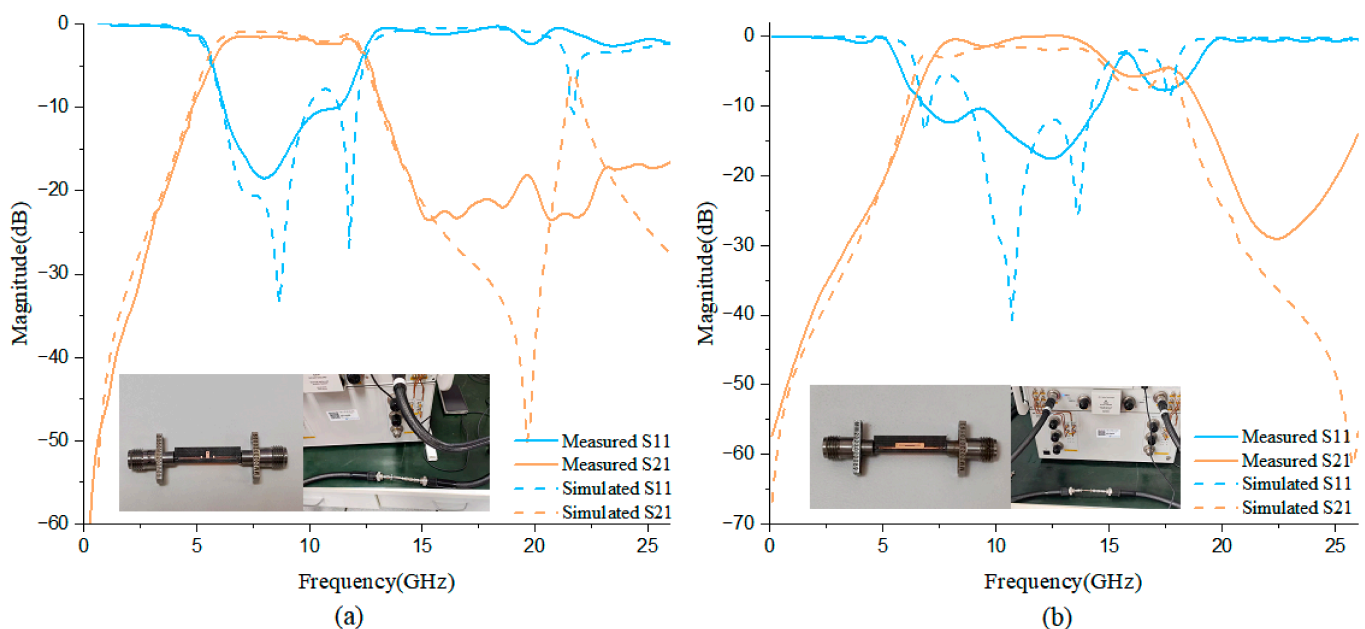


Figure 10. Experimental validation of the generated structures for two different specifications. (a) Physical testing of a filter with a center frequency of 10.5 GHz and a 3 dB bandwidth of 7–14 GHz; (b) Physical testing of a filter with a center frequency of 8.5 GHz and a 3 dB bandwidth of 5–12 GHz.

For both fabricated prototypes, the minor discrepancy in the passband (less than 0.15 GHz frequency shift) is primarily attributed to the chemical etching tolerances during PCB fabrication and the slight dielectric constant fluctuations of the F4B substrate at high

frequencies. Regarding manufacturability, since the minimum feature size of each grid pixel in our binarized dataset corresponds to 0.3 mm, the layouts are fully compatible with the etching resolution of standard commercial PCBs. Numerical tolerance evaluation shows that common over-etching or under-etching errors of ± 0.02 mm along the patch boundary only result in minor impedance shifts and fractional bandwidth changes of less than 1%. This demonstrates that the generative diffusion model implicitly favors robust topologies insensitive to manufacturing errors, thus ensuring reliable practical manufacturability. These results confirm that the “generation-evaluation-optimization” paradigm effectively achieves high-precision synthesis of microwave components from design intent to physical realization. These multi-specification physical verification results, combined with numerical validations, provide compelling evidence that our framework robustly generalizes across varying frequency bands and effectively ensures physical compliance for passive filter designs.

Furthermore, the performance of the proposed filter is compared with other recently reported designs [5–7], as summarized in Table 5. As the table demonstrates, the filter synthesized by our inverse design framework achieves the widest fractional bandwidth among the referenced works, verifying its broad ultra-wideband coverage. Concurrently, it maintains a highly competitive, low insertion loss profile within the primary passband. Regarding out-of-band rejection, the proposed design exhibits excellent and stable attenuation across the entire stopband, performing on par with or even exceeding traditional empirical designs [5–7].

Table 5. Performance comparison with other filters.

Refs.	Center Frequency (GHz)	3 dB Frequency Range (GHz)	Rejection Level (dB)	Upper Pass Band IL (dB)	Upper Pass Band FBW (%)
[5]	12.3	6.5–23	<−22	<1.7	46.81
[6]	12.795	10.215–15.375	>18	0.58	40.33
[7]	4.65	3.15–6.15	>15	<2	64.5
This work	9.04	5.67–12.40	<−20	<1.5	74.53
	10.98	7.35–14.60	>9.57	< 0.2	66.1

To evaluate the impact of surrogate model errors on the optimization process, a technical discussion regarding the framework’s robustness is detailed as follows. Firstly, the ResNet surrogate executes a holistic mapping from geometric layouts directly to electromagnetic scattering coefficients, where each evaluation is mathematically independent. This direct-mapping mechanism effectively eliminates the sequential propagation and amplification of prediction errors commonly observed in auto-regressive networks. Secondly, the genetic algorithm optimizes a highly smooth, 128-dimensional continuous latent space constrained by the conditional diffusion model, rather than executing an unconstrained search within a high-dimensional, discrete pixel space. This manifold regularization restricts generated candidates to physically realistic structural boundaries, preventing the optimization trajectory from exploiting surrogate inaccuracies or entering non-physical design regimes. Finally, the trained surrogate achieves a well-bounded validation mean squared error of 1.99×10^{-3} , ensuring that residual prediction errors manifest only as minor local fitness perturbations rather than drifting the global convergence. Combined with the final full-wave validation using ANSYS HFSS 2019 as a strict gating mechanism, this integration ensures that the final synthesized solutions remain physically valid and compliant with target specifications.

4. Conclusions

This study presents an automated inverse design framework for ultra-wideband (UWB) microstrip filters, integrating conditional diffusion probabilistic models with a ResNet-18 architecture. By constructing a comprehensive dataset comprising 12,137 pixelated geometric patterns and their corresponding *S*-parameters, we successfully established a high-precision mapping from electromagnetic (EM) specifications to physical topologies. Comparative analyses demonstrate that the diffusion model significantly outperforms GAN and VAE architectures in terms of training stability and generative fidelity. Specifically, the proposed method effectively mitigates the inherent blurriness of VAEs and the training instability of GANs, yielding geometries with high edge precision and structural integrity. The developed ResNet-based surrogate model facilitates rapid EM performance evaluation, enabling instantaneous verification within the design loop. Experimental results for both database-derived and customized targets over the 0–26 GHz range confirm the framework's robust generalization capability. The simulated responses exhibit excellent agreement with design objectives, demonstrating the model's efficacy in addressing the non-unique one-to-many mapping problem inherent in inverse design. The generated patterns not only maintain high structural diversity but also ensure the continuity and manufacturability of the microstrip lines. Furthermore, while our framework is validated on irregular patch-based configurations, its underlying mathematical formulation can be directly extended to the inverse design of practical periodic or quasi-periodic microwave structures, such as those relying on multi-mode open stubs or periodic loading networks. By configuring the pixel matrix to represent a periodic unit cell and incorporating periodic boundary conditions into the surrogate evaluator, the conditional diffusion network can efficiently capture array factor dependencies, offering a robust intelligent synthesis solution for complex periodic microwave components [28,29]. Future research will focus on several key trajectories to further improve the practical applicability and engineering robustness of the proposed framework. First, we plan to explore consistency models or latent diffusion to accelerate inference speed, while extending the framework to other passive components (such as power dividers, couplers, and antennas) to evaluate its scaling capability across unseen topologies and out-of-distribution targets. Second, to better handle non-ideal engineering inputs, future work will systematically investigate the model's tolerance against noisy target curves and incomplete frequency responses. Furthermore, to rigorously enhance uncertainty quantification beyond basic statistical intervals, advanced probabilistic frameworks, such as Monte Carlo dropout, ensemble predictors, or Bayesian neural networks will be implemented in future research. Finally, we aim to develop physics-informed diffusion models (PIDM) by integrating electromagnetic field theory, while incorporating yield analysis and fabrication perturbations directly into the design loop to ensure higher structural reliability and success rates in real-world manufacturing.

Supplementary Materials: The following supporting information can be downloaded at <https://www.mdpi.com/article/10.3390/electronics15143014/s1>. Section S1. Detailed information of the geometric training datasets. Section S2. Detailed data of the Kruskal-Wallis. Section S3. Detailed information of the training performance comparison among the three networks. Section S4. Additional samples of inverse design tests for the three networks. Section S5. Detailed Approach to the Inverse Design of Custom Filters.

Author Contributions: Conceptualization, R.X.; methodology, R.X.; software, R.X.; validation, R.X., Z.R., H.Z. and H.W.; formal analysis, R.X.; investigation, H.W.; resources, H.W.; data curation, R.X., H.Z. and Z.R.; writing—original draft preparation, R.X.; writing—review and editing, H.W.; visualization, R.X.; supervision, H.W.; project administration, H.W.; funding acquisition, H.W. All authors have read and agreed to the published version of the manuscript.

Funding: This research was supported in part by the National Nature Science Foundation of China under Grant 61801262, the Key Research and Development Program of Jiangsu Province (Industrial Foresight and Key Core Technologies) under Grant 2281082300401, the Open Research Program of State Key Laboratory of Millimeter Waves under Grant K202312, and the Startup Foundation for Introducing Talent of NUIST under Grant 2022r071.

Data Availability Statement: Data is contained within the article.

Conflicts of Interest: The authors declare no conflicts of interest.

References

1. Nouri, L.; Nkenyereye, L.; Hafez, M.A.; Hazzazi, F.; Chaudhary, M.A.; Assaad, M. A simplified and efficient approach for designing microstrip bandpass filters: Applications in satellite and 5G communications. *AEU-Int. J. Electron. Commun.* **2024**, *177*, 155189. [\[CrossRef\]](#)
2. Tahaİmeci, Ş.; Tütüncü, B.; Bešlija, F.; Herceg, L. Microstrip filters based on open stubs and SIR for high frequency and ultra-wideband applications. *J. Eng. Res.* **2022**, *10*, 212–223. [\[CrossRef\]](#)
3. Chen, Q.; Xie, C.; Cheng, R.; Dang, Z.; Liang, F.; Liao, F. An Ultra-Wideband Bandpass Filter Using Defected Ground Structure. In Proceedings of the 2024 IEEE 10th International Symposium on Microwave, Antenna, Propagation and EMC Technologies for Wireless Communications (MAPE), Guangzhou, China, 27–30 November 2024; pp. 1–4.
4. Bardak, C.; Dağlı, İ. Ultra-Wideband Microstrip Filter Design with Super-Shaped Defected Ground Structures. *Bitlis Eren Üniv. Fen. Bilim. Derg.* **2021**, *10*, 249–255. [\[CrossRef\]](#)
5. Dardeer, O.M.; Elsadek, H.A.; Elhennawy, H.M.; Abdallah, E.A. Ultra-wideband bandstop filter with multiple transmission zeros using in-line coupled lines for 4G/5G mobile applications. *AEU-Int. J. Electron. Commun.* **2021**, *131*, 153635. [\[CrossRef\]](#)
6. Li, C.; Ma, Z.H.; Chen, J.X.; Wang, M.-N.; Huang, J.-M. Design of a compact ultra-wideband microstrip bandpass filter. *Electronics* **2023**, *12*, 1728. [\[CrossRef\]](#)
7. Golestanifar, A.; Karimi, G.; Lalbakhsh, A. Varactor-tuned wideband band-pass filter for 5G NR frequency bands n77, n79 and 5G Wi-Fi. *Sci. Rep.* **2022**, *12*, 16330. [\[CrossRef\]](#) [\[PubMed\]](#)
8. Swanson, D.; Macchiarella, G. Microwave filter design by synthesis and optimization. *IEEE Microw. Mag.* **2007**, *8*, 55–69. [\[CrossRef\]](#)
9. García-Lampérez, A.; Llorente-Romano, S.; Salazar-Palma, M.; Sarkar, T. Efficient electromagnetic optimization of microwave filters and multiplexers using rational models. *IEEE Trans. Microw. Theory Tech.* **2004**, *52*, 508–521. [\[CrossRef\]](#)
10. Sato, H.; Igarashi, H. Fast multi-objective optimization of electromagnetic devices using adaptive neural network surrogate model. *IEEE Trans. Magn.* **2022**, *58*, 8202209. [\[CrossRef\]](#)
11. Koziel, S.; Pietrenko-Dabrowska, A. Low-cost quasi-global optimization of expensive electromagnetic simulation models by inverse surrogates and response features. *Sci. Rep.* **2022**, *12*, 19894. [\[CrossRef\]](#) [\[PubMed\]](#)
12. Liu, Y.H.; Liang, J.C.; Wang, B.Z.; Wang, R. Inverse design method for electromagnetic periodic structures based on physics-informed neural network with embedded analytical models. *IEEE Trans. Microw. Theory Tech.* **2024**, *73*, 844–853. [\[CrossRef\]](#)
13. Pollok, S.; Bjørk, R.; Jørgensen, P.S. Inverse design of magnetic fields using deep learning. *IEEE Trans. Magn.* **2021**, *57*, 2101604. [\[CrossRef\]](#)
14. Li, Q.; Wang, J.; Lei, T.; Xiang, T.; Qin, C.; Yang, M. Design of metamaterials for absorbers based on variational autoencoder. *IEEE Access* **2024**, *12*, 92328–92336. [\[CrossRef\]](#)
15. Zhou, J.; Zhang, J.; Xia, H.; Yang, R. Deep learning-enhanced multifunctional THz metasurfaces via conditional variational autoencoder. *Phys. Scr.* **2025**, *100*, 096006. [\[CrossRef\]](#)
16. On, H.I.; Jeong, L.; Seo, T.M.; Jo, Y.; Choi, W.; Kang, D.-J.; Park, J.-H.; Lee, H.-J. Novel method of performance-optimized metastructure design for electromagnetic wave absorption in specific band using deep learning. *Eng. Appl. Artif. Intell.* **2024**, *137*, 109274. [\[CrossRef\]](#)
17. Wang, H.; Nie, C.; Ren, Z.; Li, Y. A Generative Model-Based Method for Inverse Design of Microstrip Filters. *Electronics* **2025**, *14*, 1989.
18. An, S.; Zheng, B.; Tang, H.; Shalaginov, M.Y.; Zhou, L.; Li, H.; Kang, M.; Richardson, K.A.; Gu, T.; Hu, J.; et al. Multifunctional metasurface design with a generative adversarial network. *Adv. Opt. Mater.* **2021**, *9*, 2001433. [\[CrossRef\]](#)
19. Wang, J.; Yao, B.; Niu, Y.; Ma, J.; Wang, Y.; Qu, Z.; Duan, J.; Zhang, B. Generative adversarial networks for high degree of freedom metasurface designs. *Adv. Compos. Hybrid. Mater.* **2025**, *8*, 94.
20. Zhao, S.L.; Wu, J.F.; Chen, L.D.; Wang, M.-J.; Xiao, Z.-T. Diffusion Model Inverse Modeling and Applications to Microwave Filters. *Electronics* **2026**, *15*, 527. [\[CrossRef\]](#)
21. Ho, J.; Jain, A.; Abbeel, P. Denoising diffusion probabilistic models. *Adv. Neural Inf. Process. Syst.* **2020**, *33*, 6840–6851.

22. Nichol, A.Q.; Dhariwal, P. Improved denoising diffusion probabilistic models. In Proceedings of the 38th International Conference on Machine Learning, PMLR, Virtual, 18–24 July 2021; pp. 8162–8171.
23. Hen, L.; Yosef, E.; Raviv, D.; Giryas, R.; Scheuer, J. Inverse design of diffractive metasurfaces using diffusion models. *ACS Photonics* **2025**, *13*, 38–46. [[CrossRef](#)]
24. Zhang, Z.; Yang, C.; Qin, Y.; Zheng, Z.; Feng, J.; Li, H. Addressing high-performance data sparsity in metasurface inverse design using multi-objective optimization and diffusion probabilistic models. *Opt. Express* **2024**, *32*, 40869–40885. [[CrossRef](#)] [[PubMed](#)]
25. Tsukerman, M.; Grotov, K.; Ginzburg, P. Diffusion-Based Electromagnetic Inverse Design of Scattering Structured Media. *arXiv* **2025**, arXiv:2511.05357.
26. Tang, J.; Garcia, P.; Scott, R. Inverse Design of Metasurfaces Using Physics-Informed Diffusion Models with Spectral Constraints. *Front. Appl. Phys. Math.* **2025**, *2*, 173–181. [[CrossRef](#)]
27. Seo, D.; Um, S.; Lee, S.; Ye, J.C.; Chung, H. Physics-guided and fabrication-aware inverse design of photonic devices using diffusion models. *ACS Photonics* **2026**, *13*, 363–372. [[CrossRef](#)]
28. Moznebi, A.-R.; Afrooz, K.; Arsanjani, A. Broadband bandpass filter and filtering power divider with enhanced slow-wave effect, compact size, and wide stopband based on butterfly-shaped spoof SPPs. *AEU-Int. J. Electron. Commun.* **2022**, *145*, 154084. [[CrossRef](#)]
29. Wang, S.; Wang, W.; Chung, K.L.; Zheng, Y. An Orthogonal Quad-Beam Scanning Antenna Using 1-Bit Dielectric Modulation in Plasmonic Metamaterial Transmission Line for Traffic Monitoring Applications. *IEEE Trans. Veh. Technol.* **2025**, *75*, 2159–2168. [[CrossRef](#)]

Disclaimer/Publisher’s Note: The statements, opinions and data contained in all publications are solely those of the individual author(s) and contributor(s) and not of MDPI and/or the editor(s). MDPI and/or the editor(s) disclaim responsibility for any injury to people or property resulting from any ideas, methods, instructions or products referred to in the content.