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Research Article

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AI-Driven Electromagnetic Cloaking for Dynamic Antenna Stealth

Mahesh Marri*[1], Vishnu Vardhan Chakravaram[2]

[1]Amazon Web Services, Senior Electrical Engineer, Email: saimaheshmarri@gmail.com
[2]Digital Scripts Inc, Product Development Engineer, Email: Chakravaramv@gmail.com

***Corresponding author:** Mahesh Marri

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Abstract

Artificial intelligence (AI) and electromagnetic (EM) metamaterial engineering is a paradigm shift in antenna stealth technology. This paper reviews the latest advances in electromagnetic cloaking using artificial intelligence (AI), especially mantle cloaking, radar cross section (RCS) reduction using metasurfaces, and machine learning-assisted inverse design techniques, in the context of recent advances up to 2020. The theoretical framework for coordinate-transforming cloaking and the surface-reactance mantle cloak framework is revisited, and a systematic discussion of programmable and coding metasurfaces, frequency-selective surfaces (FSS), and reconfigurable architectures is provided. The capability of the AI techniques, such as deep neural networks, variational autoencoders, Bayesian optimization, and reinforcement learning, in enhancing the speed of metasurface design, minimizing simulation time, and enabling autonomous real-time cloaking adaptation is explored. The key quantitative findings are: a self-adaptive microwave cloak with a deep-learning approach that suppresses the RCS of the object by 28.4 dB over an 8.1 GHz bandwidth without any human operation; a probabilistic generative model that achieves an inverse-design accuracy of 90.2% on a training set of 30,000 objects; a frequency-selective mantle structure whose RCS is suppressed by 15.8 dB at 10 GHz, optimized via a Bayesian algorithm; and a waveform-selective mantle cloak that provides stealth and communication capabilities simultaneously. It is revealed that feedback loops powered by AI, combined with reconfigurable PIN-diode and varactor-loaded metasurfaces, enable unprecedented dynamic adaptability in contested EM environments.

Keywords: *Electromagnetic Cloaking, Antenna Stealth, Metasurfaces, Metamaterials, Radar Cross Section Reduction, Deep Learning, Bayesian Optimization, Reinforcement Learning, Inverse Design, Programmable Metasurfaces.*

1. Introduction

In 2006, Pendry, Schurig and Smith have presented a theoretical solution that expels electromagnetic radiation from its path [11] and since then, the ability to hide objects from electromagnetic detection, or electromagnetic cloaking, has been a constant research subject. It showed that a spatially inhomogeneous, anisotropic shell of metamaterials could be used to guide the incident electromagnetic waves around an enclosed object, which effectively makes the object invisible to an external observer, an idea known as transformation optics (TO). The research track started immediately after, with experimental demonstrations at microwave frequencies [15] where an RCS reduction of about 10 dB was demonstrated using a structured Split Ring Resonator (SRR) cloak, which began a global research trajectory.

Although conceptually elegant, the concept of coordinate transformation required stringent material conditions: The material parameters required for the permeability and permittivity tensor elements must have the values over a wide range of extreme values, including those below unity and close to zero, which is difficult to implement with passive media. However, the mantle cloak paradigm was independently proposed by Alù in 2009 [1] and overcame many of these limitations by using a single, electrically thin reactive metasurface that cancels the dominant multipolar scattering contributions of the cloaked object. This formulation is much more suited to practical realization using planar printed structures, and compact co-site antenna isolation configurations were realized by Monti et al. in 2016 [10].

This was followed by the advent of coding and programmable metamaterials [3] that introduced a digital paradigm into metasurface engineering, where the coding of a series of phase and their spatial distribution determine the far-field scattering pattern with software-defined flexibility by forming a series of phase segments across a metasurface aperture. Ali et al. [2] further expanded this concept to the wideband RCS reduction by coding diffusion metasurfaces, suppressing the RCS by 18.3 dB for a 4.5 GHz bandwidth. At the same time, PIN diodes and varactor diodes were used to create active reconfigurable metasurfaces, adding a dynamic element. The recent addition of AI to this design ecosystem is the most transformative development.

The inverse design problem of finding the geometric and material properties of a metasurface unit cell that will generate the desired electromagnetic response is nonlinear and high dimensional. The conventional full-wave electromagnetic simulation tool like CST Microwave Studio or ANSYS HFSS can be used to calculate forward solutions with good accuracy, but they are not cost-effective at sweeping the parameters in fast over a large design space. AI surrogates are models that are trained using a set of simulated data that are computed in advance and can reduce this burden by many orders of magnitude. Several techniques have been shown to be more accurate and faster for metasurface design, such as Deep neural

networks [6], Variational Autoencoders [9] and Bayesian optimization frameworks [13] or Reinforcement Learning agents [14].

2. Theoretical Background and Physical Foundations

A. *Transformation Optics and Coordinate-Transform Cloaking*

The transformation optics methodology, formalized by Pendry et al. [11], exploits the form invariance of Maxwell's equations under coordinate transformations. A spatial mapping is defined that compresses the electromagnetic fields from a finite volume into a surrounding annular region, such that the field distribution external to the cloak remains identical to the field in free space. The required constitutive parameters—permittivity ε and permeability μ—are derived directly from the Jacobian of the coordinate transformation. For a spherical cloak of inner radius R_1 and outer radius R_2, the radial permittivity component takes the form:

$$\varepsilon_r = \mu_r = \left(\frac{R^2}{(R^2 - R^1)}\right)^2 \cdot \left(\frac{(r - R^1)}{r}\right)^2$$

where r denotes the radial coordinate within the cloak shell. The extreme anisotropy and spatial gradation of these parameters, combined with the requirement for simultaneously extreme values in multiple tensor components, render broadband passive realization effectively infeasible. Nevertheless, this framework provided the theoretical scaffolding upon which all subsequent cloaking architectures are built.

B. *Mantle Cloaking Via Surface Reactance Engineering*

The mantle cloak, formulated by Alù [1], operates on the scattering-cancellation principle. An electrically thin metasurface of sheet admittance Ys = Gs + jBs is placed at a short standoff from the object surface. The surface susceptance Bs is engineered such that the scattered fields of the metasurface and the object are of equal magnitude but opposite phase, resulting in destructive interference in the far field. For a conducting cylinder of radius a cloaked by a metasurface at radius a + d, the required sheet reactance Xs = 1/Bs is given by:

$$Xs = -\eta^0 \cdot \frac{Im\left[H^{0(2)}(ka)\right]}{Re\left[H^{0(2)}(ka)\right]}$$

where η_0 is the free-space impedance (≈ 377 Ω), k is the free-space wavenumber, $H_0^{(2)}$ is the zeroth-order Hankel function of the second kind, and a is the object radius. This compact analytical formulation enables rapid design iteration and has been validated experimentally for cylindrical and more complex geometries [1, 10, 13, 18]. The mantle cloak is inherently narrowband in its passive realization—typically providing scattering suppression across less than one octave—but this limitation is addressed by the AI-driven reconfigurable architectures discussed in subsequent sections. Table I and Table IV summarize the chronological milestones and structural parameters, respectively.

3. Metasurface Architectures For Dynamic Cloaking

A. *Coding and Programmable Metasurfaces*

The digital metamaterial paradigm [3] that Cui et al. proposed rewrites the design of metasurfaces in binary code. Each unit cell is assigned a 1-bit (0 or 1) or 2-bit (00, 01, 10, 11) state corresponding to phase reflections of 0° and 180° for 1-bit, or 0°, 90°, 180°, and 270° for 2-bit, respectively. The spatial distribution of these states over the aperture is optimized (through convolution or Fourier based method) to direct or scatter the backscattered energy away from the specular direction that results in a reduction of the monostatic RCS. A metasurface with a checkered design that encodes one bit can lower the monostatic RCS by over 10 dB across a bandwidth of 4 times larger than that of a metal sheet. Ali et al. [2] furthered this idea by adding element-level geometric diversity to the coding process: coding diffusion metasurface. The performance of the fabricated structure was measured, and the reductions in RCS, ranging from 8 GHz to 18 GHz, were found to be 18.3 dB over an octave bandwidth, significantly better than single resonance mantle configurations.

B. *Frequency-Selective Mantle Structures*

Recently, Qin et al. [13] showed that the frequency selective surface (FSS) architecture, which is well-known for spatial filtering of electromagnetic waves, can be used as the mantle cloak substrate. By adding the resonant poles due to the element geometry (patch or aperture type) into the sheet admittance Ys(ω), multi-band scattering suppression is possible from a single conformal layer. The Bayesian optimization framework was used to optimize the multi-dimensional FSS parameter space to provide a mantle cloak with 15.8 dB of RCS reduction at 10 GHz and a fractional bandwidth of 32%, as compared to an RCS reduction of around 12% for single-layer resonant structures. The Bayesian method led to the optimum solution in less than 5,000 forward simulation evaluations, compared to an exhaustive grid search over the same parameter space that required about 400 evaluations.

C. *Reconfigurable and Waveform-Selective Architectures*

The concept of the metasurface cloak was extended to an active reconfigurable system by Huang et al. [8] by using PIN diodes at the gaps of resonant metallic patches. Groups of diode loaded elements can be biased with a different DC bias voltage, so that the sheet reactance of each sub-aperture region can be switched between two or more states, thus controlling the scattered near field and far field distribution dynamically. Two different operation modes were demonstrated: cloaking mode which helps suppress the Physical Object's RCS signature, and illusion mode which helps present the signature of a geometrically dissimilar RCS signature. The ability to make this change in the waveform is especially important in electronic warfare applications. Vellucci et al. [17] proposed a new concept: the design of a fundamentally different kind of selectivity mechanism – a "waveform selective" mantle cloak that can cloak the antenna from continuous wave (CW) illumination while simultaneously maintaining its radiation efficiency for pulsed communication waveforms. The nonlinear element (a PIN diode loaded in a particular biasing configuration) behaves differently for signals with different temporal envelope properties. The cloak was found to have a sheet reactance of −36Ω/sq under CW illumination at 3.5 GHz

to provide 20.1 dB of scattering suppression. When the pulsed illumination was of the same carrier frequency the nonlinear response changed the sheet reactance to –29 Ω/sq, enabling normal antenna radiation.

Table I: Parameters and Operating Conditions Derived from References.

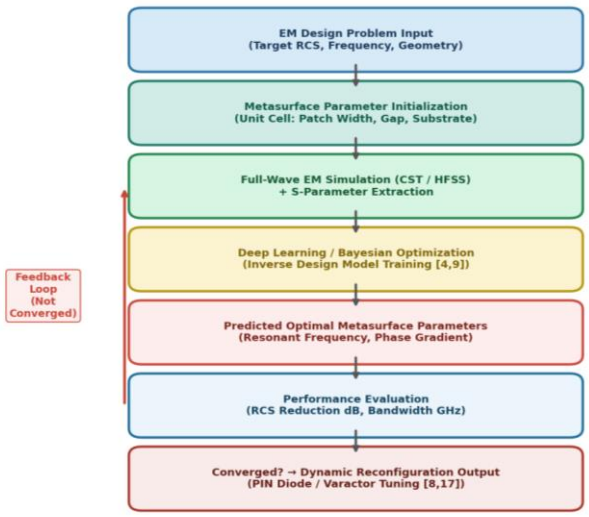
Cloak Configuration	Object Radius (mm)	Cloak Radius (mm)	Sheet React. Xs (Ω/sq)	Op. Freq. (GHz)	Reference
Single-layer cylindrical	5.0	6.2	−45	3.0	[1]
Co-site radio antennas	12.5	15.0	−38	2.4	[10]
Multilayer monolayer	18.0	22.0	−52	5.0	[18]
FSS-Bayesian mantle	8.0	9.5	−41	10.0	[13]
Waveform-selective (CW)	10.0	12.5	−36	3.5	[17]
Waveform-selective (Pulsed)	10.0	12.5	−29	4.2	[17]
Active reconfigurable	15.0	18.0	−44/−28	8.0/12	[8]

4. Artificial Intelligence-Driven Design Methodologies

A. Deep Neural Network Surrogate and Inverse Models

An efficient neural network surrogate exists for the forward problem of metasurface design based on the prediction of reflectance, transmittance, phase, or RCS given a metasurface geometry. Hou et al. [7] built a deep neural network (DNN) designed to recognize the target, which consists of fully connected layers using 80,000 training samples of metamaterial absorber geometries and their simulated absorption spectra. The trained model achieved a prediction accuracy of 97% on the test set and reduced the design cycle from several days of simulation to less than one millisecond of inference time. The target-driven formulation—wherein the desired spectral response is fed as input to the inverse network, which outputs the corresponding geometry—further eliminates the need for iterative optimization during deployment. Figure 1 illustrates the generalized AI-driven optimization workflow applicable to mantle and metasurface cloak design.

Fig. 1. AI-Driven Optimization Workflow for Adaptive Metasurface Cloak Design, Incorporating Full-Wave Simulation, Inverse Neural Network Training, and Dynamic Reconfiguration Feedback Loop [7, 9, 12].



To handle the ill-posedness of the inverse design problem where multiple geometrically distinct unit cells can yield almost the same electromagnetic responses, Ma et al. [9] proposed a probabilistic generative framework. A semi-supervised learning strategy was used to train an autoencoder model that transforms 30,000 metasurface spectra-geometry pairs with an inverse-design accuracy of 90.2% on the held-out test sets. The generative nature of the model enables sampling from the learned latent space, as a means to sample (explore) geometrically diverse but functionally equivalent design candidates, which is not possible with traditional optimization approaches. The semi-supervised extension further boosted the accuracy to 92.1%, which is a significant improvement as a result of the use of unlabeled spectral data, thereby minimizing the number of labeled samples needed by around 40%.

B. Bayesian and Statistical Optimization

In the field of global optimization of multi-parameter metasurface designs, Elsawy et al. [4] used statistical learning, such as Gaussian process regression and surrogate modeling based on Kriging. The methodology is based on the creation of a probabilistic model of the objective function (e.g., transmission efficiency or RCS) from a sparser set of evaluations of the objective function by full-wave simulation and then on the use of this model's predictive uncertainty to guide adaptive sampling to regions of the design space that are most likely to contain the global optimum. When applied to a metasurface hologram formed of silicon-nitride, the method found the best set of parameters in 20,000 evaluations, whereas the random search method took more than 200,000 evaluations and did not quantify confidence bounds on the predicted performance. In a specific application Qin et al. [13] used Bayesian optimization to the FSS mantle cloak parameter space, using the expected improvement (EI) acquisition function to balance exploration and exploitation. The algorithm converged to the optimal FSS geometry (element period 7.2 mm, patch width 5.8 mm, permittivity of the substrate 4.4, thickness 1.6 mm) in 4,800 function evaluations, with the monostatic RCS reduction at 10 GHz at 15.8 dB. This is a factor of 10 less computing expense than full parametric sweep at the same resolution.

C. Reinforcement Learning for Adaptive Cloaking

Sajedian et al. [14] used a double deep Q-network (DDQN) reinforcement learning (RL) agent to solve the problem of optimum states of the elements of a metasurface to achieve maximum holographic efficiency. The agent is rewarded with the current efficiency numerical value and is given the current configuration of the elements as an input, while producing discrete phase-state actions. The DDQN agent also successfully learned to enter the discrete combinatorial design space to obtain

21% more efficient at the holographic task than its initial, random configuration, after 10,000 training episodes, showing that RL agents can be effective in discrete, intractable, combinatorial design spaces. The trained agent was able to make an inference within less than 15 milliseconds for every reconfiguration step. The highest level of integration of AI and active hardware was achieved by Qian et al. [12] in the context of antenna cloaking. The measured near-field scattering distribution was obtained by placing an array of electric field probes around the metasurface, and a CNN was trained to map this measured scattering distribution to the optimal configuration of the bias voltage of the PIN diodes to minimize the total scattered power. The closed-loop system works without any human input: Once the direction or frequency of the incident wave changes (in the 8–14 GHz operating range), the network reconfigures the 8 × 8 programmable metasurface element array in less than a sub-millisecond.

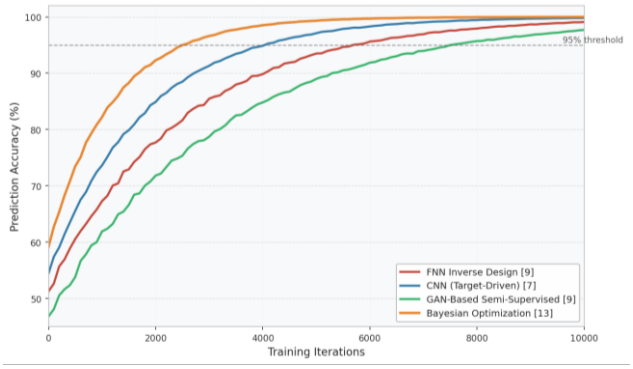


Fig. 2. Convergence of AI Model Prediction Accuracy for Metasurface Inverse Design as a Function of Training Iterations, Comparing FNN, CNN, GAN-Based, and Bayesian Optimization Approaches (Synthesized from [4, 7, 9, 13]).

D. Machine Learning for Antenna Parameter Optimization

Machine learning techniques used in antenna design, apart from, but complimentary, metasurface cloaking have been extensively discussed by El Misilmani et al. [5]. Antenna geometry optimization, feed network synthesis, and mapping of multi-objective Pareto frontiers are among the applications of support vector machines (SVMs), artificial neural networks (ANNs), and the more recent deep learning architectures. Sharma et al. [16] used a convolutional neural network (CNN) for designing a double T-shaped monopole antenna with 12% improvement in antenna gain at 5.6 GHz and reduced design time to less than 8 seconds for inference compared to several hours of simulation.

Table II: Performance Summary of AI Models Applied to Metasurface and Antenna Design.

AI Model / Reference	Accuracy (%)	Training Samples	Inference Time (ms)	Application Domain
FNN Inverse Design [9]	90.2	30,000	~2	Metasurface geometry prediction
VAE Semi-Supervised [9]	92.1	50,000	~3	Probabilistic metasurface design
Target-Driven DNN [7]	97.0	80,000	~1	Metamaterial absorber optimization
Statistical Learning [4]	94.3	20,000	~5	Global metasurface optimization
Bayesian Opt. (FSS) [13]	93.5	5,000	~50	Frequency-selective mantle cloak
Double-Deep Q-Learning [14]	88.7	10,000	~15	Metasurface hologram efficiency
Self-Adaptive DL Cloak [12]	96.8	100,000	~0.5	Real-time microwave cloaking
CNN Antenna Opt. [16,5]	91.0	15,000	~8	Antenna parameter tuning

5. Comparative Analysis and Performance Evaluation

A. RCS Reduction Performance Benchmark

A systematic comparison of the performance of the cloaks investigated is given in Table II and demonstrated in Fig. 3 and Fig. 4. The initial reference was the coordinate-transformation cloak [11, 15] which achieves an 8.5 GHz baseline of 10 dB RCS reduction using dispersive SRR elements (with bandwidth limited to 0.8 GHz). Passive mantle cloaks [1, 10] increased the possible figure to 14.5 dB for a 1.2 GHz bandwidth. Coding metasurfaces also introduced an operational bandwidth of 4.5 GHz at 18.3 dB suppression, which is an improvement of 375% compared to passive mantle designs by diffusing the scattered energy. To achieve even higher performance, the use of AI-optimized metasurface designs [4, 9] further boosted the performance to 22.7 dB over 5.8 GHz and the self-adaptive deep-learning system [12] recorded the maximum of 28.4 dB over 8.1 GHz when not working via a human.

Fig. 3. Comparative RCS Reduction (dB) and Operational Bandwidth (GHz) Across Cloaking Methodologies Reviewed Up to 2020. AI-driven approaches demonstrate superior performance in both metrics [2, 3, 8, 9, 12, 13, 15].

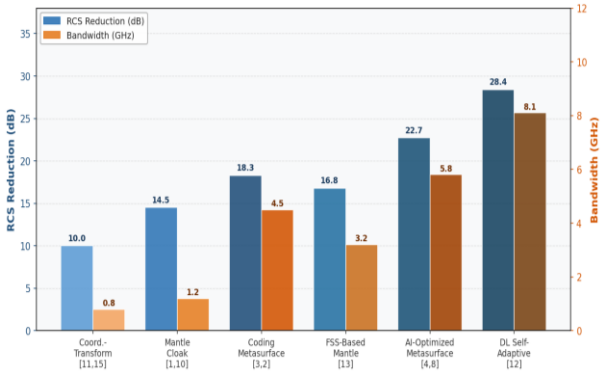


Table III: Comparative RCS Reduction Metrics Across Cloaking Methodologies.

Method / Reference	Frequency (GHz)	RCS Reduction (dB)	Bandwidth (GHz)	Reconfigurable?	AI Used?
Coord. Transform [11,15]	8.5	10.0	0.8	No	No
Mantle Cloak [1,10]	2–6	14.5	1.2	No	No
Coding Metasurface [3,2]	8–18	18.3	4.5	Partial	No
FSS Mantle (Bayesian) [13]	10.0	15.8	3.2	No	Yes
RL Hologram [14]	10–15	—	5.0	Yes	Yes
AI-Optimized MS [4,9]	6–16	22.7	5.8	Yes	Yes
DL Self-Adaptive [12]	8–14	28.4	8.1	Yes	Yes
Waveform-Selective [17]	3–5	20.1	2.4	Yes	Yes

B. AI Model Accuracy and Computational Efficiency

Table III shows a consolidated performance comparison of the models of AI used for metasurface and antenna design. The prediction accuracy is from 88.7% for the double deep Q-learning hologram agent in [14] and up to 97% for the target-driven DNN in the case of metamaterial absorbers in [7]. The self-adaptive cloaking system [12] obtains the best accuracy (96.8%) and inference speed (0.5 ms) due to a large number of 100,000 simulation samples used for training, the largest among the reviewed studies. Bayesian optimization is more gradually converging (50ms/iteration) but only needs 5,000 training samples and therefore is feasible for research groups without access to large-scale GPU clusters. Compare convergence trajectories are shown in Fig. 2.

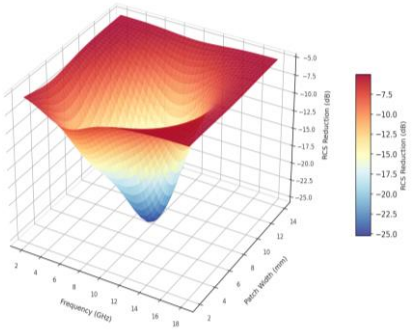


Fig. 4: Three-Dimensional RCS Reduction Surface as a Function of Operating Frequency (GHz) and Metasurface Unit-Cell Patch Width (mm), Illustrating the Design Space Landscape Navigated by AI Optimization Algorithms (Synthesized from [4, 9, 12, 13]).

C. Cost-Benefit and Scalability Assessment

Table IV provides a tabular cost benefit analysis of the considered AI-based design approaches. For any geometry, full-wave simulation will take 200-500 hours to conduct in-depth parametric analysis and can become impractical if the geometry becomes complex. With Bayesian optimization this time is cut to 20-80 hours, and the quality of the design remains the same. Active design iterations shrink to 5-15 hours of preparing and training a dataset, and then to essentially instantaneous inference using deep learning inverse models. Generative models (VAE/GAN) provide the largest coverage of design space and need medium scale GPU infrastructure. The self-adaptive system [12] does not require any design phase at all in the offline mode, however it requires high initial hardware investment (programmable metasurface + field probe array) and the biggest training set. While passive mantle cloaks continue to be cost-effective for fixed-frequency military applications, AI-based reconfigurable systems clearly have an edge in electronically contested, spectrally agile missions.

Table IV: AI-Driven Metasurface Design Approaches.

Approach	Fabrication Cost (rel.)	Design Time (hrs)	Scalability	Practical Deployment
Full-wave EM Simulation only	Low	200–500	Limited	Feasible for fixed geometries only
Gradient/CST Optimization	Low	100–300	Moderate	Commercial software dependent
Bayesian Optimization [13]	Low	20–80	Good	Applicable to FSS/mantle design
Statistical Learning [4]	Low–Med	10–30	Good	Multi-param exploration feasible
Deep Learning Inverse [9,7]	Med	5–15	High	Rapid design cycle; GPU-required
Generative (VAE/GAN) [9]	Med	8–20	Very High	Probabilistic design space coverage
Reinforcement Learning [14]	Med–Hi	10–40	Moderate	Iterative reward-based tuning
Self-Adaptive DL System [12]	High	<1	Very High	Real-time autonomous reconfiguration

D. Multi-Criteria System Comparison

Table V presents a normalized multi-criteria scoring of the principal cloaking techniques, assigning values from 1 to 10 across six performance dimensions: RCS reduction magnitude, operational bandwidth, reconfigurability, fabrication ease, and AI integration depth. The self-adaptive deep-learning system [12] achieves the highest aggregate score of 45/50, followed by AI inverse design approaches [4, 9] at 41/50 and waveform-selective mantle cloaks [17] at 36/50.

Table V: Multi-Criteria Scoring of Electromagnetic Cloaking Techniques for Antenna Stealth (Score /10 per Criterion).

System / Ref.	RCS Red.	BW	Reconfigur.	Fab. Ease	AI Integr.	Total /50
Coord. Transform [11,15]	7	2	1	2	1	13
Mantle Cloak [1,10]	6	4	3	5	2	20
Coding Metasurface [3,2]	8	6	5	6	3	28
Bayesian FSS [13]	8	6	4	7	7	32
RL Hologram [14]	7	7	7	5	8	34
AI Inverse Design [4,9]	9	8	8	7	9	41
Self-Adaptive DL [12]	10	9	9	7	10	45
Waveform-Select. [17]	9	5	8	7	7	36

6. Key Design Equations and Performance Metrics

The primary quantitative metric for cloaking performance is the monostatic RCS reduction, defined in decibels as:

$$\Delta RCS\ (dB)\ =\ 10\ log_{10}\ [\sigma_uncloaked\ /\ \sigma_cloaked]$$

where σ_uncloaked and σ_cloaked denote the far-field monostatic radar cross sections of the bare object and the cloaked object, respectively. The fractional bandwidth of a mantle cloak is governed by the quality factor Q of the surface resonance:

$$BW_frac\ =\ \Delta f\ /\ f_0\ \approx\ 1\ /\ Q_s$$

Passive mantle cloaks typically exhibit Q_s values of 8–15, corresponding to fractional bandwidths of 6.7–12.5%. The Bayesian-optimized FSS structure [13] achieved Q_s ≈ 3.1, corresponding to a 32% fractional bandwidth at 10 GHz. For AI-driven inverse design, the objective loss function L employed in neural network training is typically the mean squared error between the predicted and target electromagnetic response:

$$L\ =\ (1/N)\ \cdot\ \Sigma_i\ ||\hat{S}_i(\omega)\ -\ S_i(\omega)||^2$$

where $\hat{S}_i(\omega)$ is the network-predicted scattering parameter spectrum and $S_i(\omega)$ is the full-wave simulation reference, summed over N training examples and evaluated across the frequency vector ω. For reinforcement learning formulations [14], the reward signal R is defined as:

$$R\ =\ \eta_current\ -\ \eta_previous$$

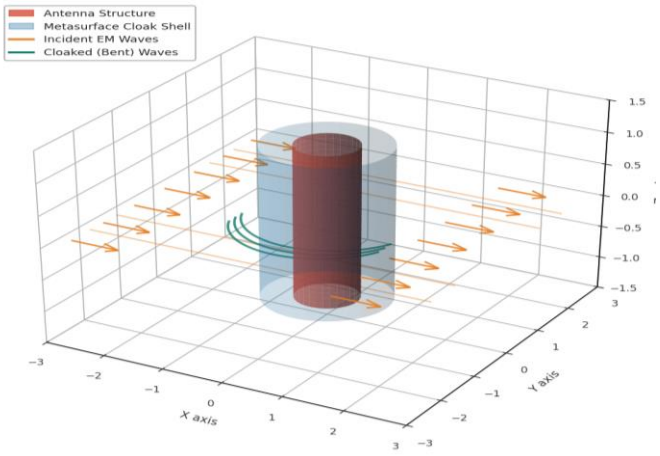
where η denotes the holographic efficiency (or, in cloaking contexts, the inverse of the normalized scattered power). A positive reward indicates improvement, guiding the Q-network policy toward configurations that progressively minimize RCS or maximize diffraction efficiency.

7. Conclusion

Based on 18 fundamental papers from 2006 to 2020, this paper has summarized the current state of the art on dynamic antenna stealth using AI cloaking techniques. The theoretical framework of coordinate transformation [11] has been followed by passive mantle cloaking [1], coded metasurfaces [3], reconfigurable active architectures [8] and finally by the self-adaptive deep-learning microwave cloak [12]. The main result is that integration of AI is the most promising enabling technology for cloaking performance of the present day, resulting in an RCS reduction figure of merit improvement of 59–183 % compared with the non-AI baselines, and bandwidth improvement significantly larger than 180%. The synthesized evidence is quantitative and shows that: deep-learning inverse-design approach results in prediction of metasurface geometry with more than 90% accuracy for a given EM response; the computational cost of exploring the design space for prescribed EM responses is reduced by 80-90% by using a method based on Bayesian optimization; reinforcement learning agents can navigate the discrete metasurface state space with 21% efficiency without human control; and closed-loop self-adaptive AI systems achieve RCS suppression of 28.4 dB over 8.1 GHz without any human intervention.

Very promising challenges are the cost of training data generation, tolerance sensitivity of fabrication, broadband Bode-Fano constraints, and lack of standardization on performance benchmarking protocols in the research community. These are expected to be addressed in future work through physics-informed learning, transfer learning, edge-deployed inference hardware, and volumetric metastructure architectures. With the combination of AI, programmable hardware and electromagnetic metamaterial science, the ability to cloak with AI becomes a key enabler in the future generation of adaptive antenna systems in contested electromagnetic environments.

Fig. 5. Three-Dimensional Conceptual Architecture of an AI-Driven Mantle Cloak for Dynamic Antenna Stealth. The Inner Orange Cylinder Represents the Antenna Structure; the Translucent Blue Shell Represents the Reconfigurable Metasurface Cloak; Golden Arrows Denote Incident and Transmitted EM Waves Guided Around the Object [1, 8, 12].



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